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THESIS

DEVELOPMENT OF A METHODOLOGY TO OPTIMALLY
ALLOCATE VISUAL INSPECTION TIME

by

Monroe P. Warner

June 1989

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The model is used in a goal program to optimize the use of inspector time in a production facility. The model and the goal program are applied to a military problem to demonstrate the broad applicability of the methodology. The military problem is the allocation of inspection time before firing an artillery weapon to insure accurate and timely delivery

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DEVELOPMENT OF A METHODOLOGY TO OPTIMALLY ALLOCATE VISUAL INSPECTION TIME

by

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Submitted in partial fulfillment of the requirements for the degree of

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ABSTRACT

Many production facilities rely on the intuition of the quality assurance inspector for determining what will be visually inspected and for what length of time on a finished product. In this thesis a model for visual inspection of a finished product is developed. The key parameters in the model are the probability of worker error, the probability of inspector error, and the cost of system error. Paired comparisons of error phenomena from operational personnel are converted to probabilities using the indirect numerical estimation technique.

The model is used in a goal program to optimize the use of inspector time in a production facility. The model and the goal program are applied to a military problem to demonstrate the broad applicability of the methodology. The military problem is the allocation of inspection time before firing an artillery weapon to insure accurate and timely delivery of projectiles.

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I. INTRODUCTION

A. GENERAL

Assume that all the resources needed for a particular production process are already purchased. They represent sunk costs to the production facility. The only cost of doing business then is the cost incurred by producing unacceptable goods. If finished goods are flawed or late when delivered to the consumer in a market economy then the producer eventually loses market share. Continued loss of market share leads to annihilation of the production business. Thus, the decision maker's task is to allocate the available resources to achieve timely delivery of error-free products. This is the situation in which some mid-level managers find themselves. In other words, given little or no control over the resources on hand, they are to perform as well as possible but are not to fail.

The typical response to the mid-level manager's production problem is to employ part of the allotted labor resources as quality assurance inspectors. Use of labor resources as inspectors rather than producers decreases production. The time required to conduct the inspections slows the remaining production. The use of the inspectors, however, decreases the number of flaws in the finished product. The manager faces

a tradeoff between two favorable objectives: better finished products versus more finished products.

Assume that all worker errors in the production process that can lead to a flawed finished product can be identified. Assume that each worker $error_i$ (where $i = 1,...,m$) is independent and mutually exclusive of each other. Therefore, given that a flawed product is found bearing the effects of one error from the production process:

$$(1\text{-}1) \qquad \sum_{i=1}^{m} P\ (error_i) = 1.0$$

Assume a cost distribution can be identified for error. From those distributions assume that mean costs can be derived. Now the expected cost of doing business (EC) per each item produced can be written:

$$(1\text{-}2) \qquad \sum_{i=1}^{m} P\ (error_i) * C\ (error_i) = EC$$

where m is the number of independent errors

P is "probability"

C is "mean cost"

The probability for a flawed finished product due to error on $task_i$ [$P\ (error_i)$] is the probability that both the worker erred on the task and the inspector failed to identify the worker's error. The inspector's ability to positively identify flawed products as being unacceptable increases over

time. Naturally, the cost of doing business can be reduced if the allocation of available inspector time can be driven toward errors that occur more frequently and which have greater cost. How should the available inspection time be divided between error-prone tasks to best reduce the cost of doing business? The focus of this thesis is how to allocate the available inspection time to best accomplish the manager's multiple objectives of speed and thoroughness.

Goal programming is a convenient tool for simultaneously satisfying several objectives. The first half of this thesis proposes a methodology for allocating inspection time based on goal programming. The second half uses the artillery gun chief's inspection problem to illustrate the methodology.

In offering a solution to the allocation of inspection time problem, the thesis uses several timely, efficient, and sound techniques to derive a deterministic probability for worker failure on each error-prone task, the expected time that an inspector spends inspecting each task, and the cost distribution of error on each task. The hope is that these techniques are sufficiently convenient that they can be readily adopted by mid-level managers in their allocation of inspection resource problems.

B. DEFINITIONS

Some terminology is peculiar to the study of human reliability. Other terminology is peculiar to the U.S. Army and the field artillery. Appendix F contains a glossary of those terms.

C. ORGANIZATION OF THE THESIS

Chapter 2 presents the experimental results and theories that are the underpinnings of the proposed methodology for solving the allocation of inspection time problem. The chapter documents alternative techniques by which error rates and time estimates may be derived other than by empirical observation. The chapter reviews a technique for estimating costs of errors and discusses the attributes of goal programming.

Chapters 3 through 5 present the problem that illustrates the proposed methodology. Chapter 3, Background to the Artillery Problem, describes the allocation of inspection time problem as it applies to the gun section and the artillery fire support system. The discussion of artillery explains the tasks of the various crewmen and the errors they make. Chapter 4 develops a model for the artillery gun chief's problem. Chapter 5 applies the methodology to an active army unit at Fort Ord, California. Chapter 6, Conclusions and Recommendations, proposes other applications of this

methodology and suggests areas for future research. The appendices give the output from the computer runs discussed in Chapter 5, the surveys of respondents, and step-by-step procedures for computing the solution to the artillery gun chief's inspection problem.

II. DEVELOPMENT OF A VISUAL INSPECTION MODEL

A. GENERAL

1. Need for a Model over Intuition

Often the allocation of inspection time to various inspection tasks is determined by the inspector. It is generally expected that an inspector will employ his full experience, knowledge, and intuition when deciding how to spend his time on the various visual inspection tasks he must perform. Intuition is inadequate for such tasks as allocating inspection time. Hogarth identifies the primary weakness in reliance on intuition in general:

> One could suppose that through intuitive judgment people are able to capture important information which escapes codification and is thus not amenable to statistical analysis. Indeed, intuitive judgment does capture much information, however, it is inconsistent. Moreover such inconsistency necessarily attenuates human predictive validity. In other words, although humans may on occasion exhibit high accuracy in judgment, inability to apply judgmental rules consistently across a series of cases means that on average models outpredict people. [Ref 2, p.194]

Over the long run, a model that incorporates all available knowledge regarding inspection phenomenon and allocates inspection time accordingly will outperform any inspector's intuition.

A mathematical model of the inspection process offers many advantages over reliance on the intuition of an inspector. First, a model offers a means to understand the underlying causes and effects occurring in the inspection phenomena. Reliance on inspector's intuition offers no alternative method to solve inadequacies should intuition start failing. With a model there is the means to test alternative solutions. Gass states,

> It (a mathematical model) enables us to evaluate the effects of a change of one variable on all the other variables; it provides us with a quantitative basis to sharpen and evaluate our intuition of the process under investigation... Mathematical models enable us to bring some semblance of scientific methodology to areas of decision making heretofore characterized by intuition and experience. [Ref 42, p.26-27]

Morse and Kimball write, "Operations research is a scientific method of providing executive departments with a quantitative basis for decisions regarding operations under their control [Ref 19, p 7]." Building effective mathematical models of the inspection process allows managers to take control of their inspection resources and make optimal use of them in support of production facility goals and values. If inspectors are not brought in to support the goals and values of the production facility they are apt to pursue their own set of goals and values. Hillier and Lieberman allude to what then tends to happen "...(there is) a tendency for many components of an organization to grow into relatively

autonomous empires with their own goals and value systems [Ref 5, p 3]."

Inspector time is a resource of the manager and, as such, it should support the production facility's goals and values. If the manager can quantify his goals with respect to product quality then goal programming allows him to model his inspection time problem. The model gives him the means to simultaneously consider his goals and allocate inspector's time to satisfy those goals.

2. Modeling of the Inspection Process

The purpose of the inspection process is to identify worker errors that affect the system. The model of the inspection process must incorporate the effect that the errors potentially have on the system. Thus, a large part of modeling the inspection process is error analysis.

The importance of an error is directly related to its potential for unacceptable system effects. The Nuclear Regulatory Commission (NRC) makes this point in regard to errors in general:

> The importance of an error is a function of its frequency, the efficiency of the (inspector) for the error, and the likelihood and severity of the potential consequences of the error... [Ref 14, p 4-17].

In applying this same concept to the realm of human error, Pickrel and McDonald write:

> The extent and cost of efforts to eliminate sources of human errors should be commensurate with:
>
> 1) the frequency with which the error is expected to occur;
>
> 2) the frequency with which a (system) failure will occur as a result of the error; and
>
> 3) the possible consequences of the failure condition. [Ref 27, p 649]

Swain points the direction for the modeling of the inspection process when he writes:

> Errors are important only if they lead to important consequences. Thus, the steps in error analysis are
>
> a) Identify the consequences of interest;
>
> b) Identify all errors that can lead to those consequences;
>
> c) Determine error rates for each class of errors;
>
> d) Identify the likely contributing factors. [Ref 10, p.14]

The probability of worker error, the probability of associated inspector error, and the cost of associated product flaws are the parameters needed to establish the relative importance of the different errors. These parameters must then be brought together in one model to represent the inspection process.

This chapter reviews the rationale for using the opinions of subject-matter experts to both estimate the probability for worker error and to estimate the time required to inspect for that worker error. Theories and experiments dealing with the probability for inspector failure as a

dealing with the probability for inspector failure as a function of time to inspect and a method for cost estimation of system error are reviewed.

Another area discussed in the model development is the importance of internal consistency in judgments made by subject-matter experts before their subjective evaluations have merit. Saaty's Analytical Hierarchy Process [Ref 17] is reviewed for its method of evaluating the internal consistency in a respondent. Also, in this chapter, goal programming is reviewed as a means to model problems such as the allocation of inspection resources problem. The goal program that achieves this allocation of inspector time is relatively simple and straightforward. The challenge is developing the probabilities for error and the costs of error required by the model and the goal program.

B. THE PROBABILITY OF CREW ERROR

1. Rationale for Subjective Evaluations

Research into human reliability and error analysis led to work by the Nuclear Regulatory Commission (NRC) in its evaluation of human error probability in the operation of nuclear power plants. The NRC is at the forefront in research on human error and design of functional, safe systems that incorporate human error rates.

Traditional thinking is that personal opinion of people with working experience is worth little as a basis for good operations research work. Morse and Kimball were emphatic about this when they helped found operations research:

> The opinions of a few dozen persons who have had operational experience provide an extremely shaky foundation for any operations research...The need for unbiased, impersonal facts, not opinions, must always be borne in mind. [Ref 19, p 8-9]

This influence is still clear today as there is often an aversion to using operational experience as a basis for operations research. Echoing the sentiments of Morse and Kimball is the following more recent comment by Von Winterfeldt and Edwards that typifies the views of many systems analysts about the appropriate way to assess probabilities:

> By far the most common practical procedure for assessing probabilities is to collect a large set of observations and then to use a relative frequency. This procedure is tedious but the existence of empirical science testifies to its success.[Ref 29, p. 110]

Whereas probabilities for equipment failure may be best established by the strict empirical approach, it is unlikely that probabilities for human failure (human error) can be gathered in that manner. Swain and Miller provide a discussion of the reasons human error data generally cannot be obtained through empirical observations [Ref 1, p 226].

Horley and Giordano give a graphic example of failure of the empirical approach to obtain human error data on artillery gun sections in U.S. Army tests conducted at Fort Hood, Texas [Ref 15, p.67-73]. Swain and Guttman discuss why the empirical approach to generating human error data has not worked in nuclear power plants:

> The collection of relative frequencies (for human error rates by empirical observation) is impractical for several reasons.
>
> First, error probabilities for many tasks are very small. Therefore, in any reasonable time period, not enough errors will occur to permit the fitting of a meaningful distribution to the observed error relative frequencies.
>
> Second, usually there is some penalty associated with the commission of an error, which discourages the identification of individuals who commit the errors. If such identification were insisted upon, there would be some unknown, but sizeable, number of errors not reported.
>
> Third, the administrative problems and costs of recording and analyzing errors by person would probably be unacceptable. [Ref 14, p. 6-2]

There are numerous activities in need of human reliability data for enhanced man-machine system design. In most of these activities there is extensive operational experience, but there is little or no human error data. Expert judgment provides a means to generate human error data. Swain states,

> The use of collective judgment by subject-matter experts is one way to make up for the paucity of empirical error rate data. Studies indicate that it would be feasible to have a number of people with detailed knowledge of various

tasks in an industrial setting rank-order tasks in terms of error-likeliness. [Ref 10, p.101]

Miller and Swain briefly describe how the methods that use expert judgment to generate human error data are structured:

> Subject-matter experts judge the relative or absolute likelihood of error for several task descriptions, and these responses are converted to usable human error probabilities by mathematical scaling techniques. [Ref 1, p. 238]

The NRC endorses four methods for eliciting expert judgment input to estimate human error probabilities. The NRC makes the following exhortation in regards to these methods:

> Make the best use possible of current procedures and information, even though they may be flawed...These (the four methods endorsed by the NRC) are based on sound psychological theory and empirical support that indicate their potential usefulness. And as a practical matter, they can be used now to obtain needed human error probabilities. [Ref 14, p 8-6]

The NRC approved methods are the paired comparisons procedure, ranking and rating procedure, direct numerical estimation procedure, and indirect numerical estimation procedure. Swain and Guttman [Ref 14, p.8-6 to 8-13] and Seaver and Stillwell [Ref 28, p A-2 to A-51] provide detailed explanations of each of the NRC approved methods.

2. Experts to Supply Expert Judgment

Embrey noted that his whole approach to developing human error probabilities by subjective input was contingent on judges. He writes:

> The success of the approach is likely to be critically dependent on the knowledge and experience that the judges

> possess regarding the tasks they are asked to assess. For this reason it is very important that strenuous attempts are made to obtain appropriately qualified judges. [Ref 28, p. 30]

In commenting about eliciting judgments of uncertainty (or probabilities) from people, Von Winterfeldt and Edwards write:

> If a numerical measure of uncertainty is an opinion, it characterizes a person as well as an event; we want to elicit from the right person. Who is that?..[Ref 29, p. 113]

The "right person" is the one who has the best understanding of the phenomenon under investigation and who can best relate that understanding in terms that can be quantified.

Swain offers that the worker or inspector himself is an expert on error rates:

> Subject-matter experts are persons who are especially knowledgeable about the tasks for which error rates are to be derived. Thus, if one wanted to derive error rate estimates for new tasks in an assembly plant, the experts would be persons who perform or had performed similar tasks in an assembly plant. [Ref 10, p.101]

Saaty agrees. Saaty not only allows that the worker or inspector is an expert in the operational aspects of his work, but he implies that he also is the best person for relating to others phenomena about that work:

> We generally agree that people who experience a phenomenon firsthand are the ones who can best shed light on our understanding of it; indeed, knowledge derived from experience is basic to all understanding. [Ref 17, p. 9]

Lai, Shenoi, and Fan suggest that workers and inspectors are specifically well-equipped to estimate probabilities concerning errors and hazards:

> One of the major problems facing many quantitative risk assessment studies is the lack of proper data about the probabilities of occurrence of hazardous events. Often, the only alternative is to employ rough estimates provided by operations personnel.... Human beings often possess quality knowledge that arises out of their insights and experiences. When the safety of a system is being examined this expertise has the greatest weight. [Ref 40, p.136]

While the worker and inspector are certainly experts on the operational aspect of the human error phenomenon that is a subject of this study, the question remains whether they can relate this expert understanding in terms that permit quantification.

3. Indirect Numerical Estimation Technique

Miller and Swain write that a major disadvantage of methods that use expert judgment to generate human error data is that the expert often lacks sufficient familiarity with probabilities to be able to give meaningful input [Ref 1, p. 244]. Persons with operational experience, such as workers and inspectors, are often not qualified to give a direct numerical estimate of a probability. Paulos states, "An appreciation for probability takes a long time to develop. [Ref 7, p.133]." Morse and Kimball warn, "People seldom estimate random events correctly...their opinions are nearly

always unconsciously biased [Ref 19, p. 8]." Swain cautions:

> It is not suggested that (subject-matter) experts be asked to make estimates of actual error rates for tasks. Such estimates would tend to vary widely and would generally underestimate the true error rates. Some subject-matter experts simply would refuse to make such estimates. [Ref 10, p 101]

Hogarth states,

> People do have difficulty in expressing their degree of knowledge in the precise quantitative form demanded by probability theory.... Numerous studies have shown fallibilities in intuitive attempts to guess probabilistic relations from given facts. [Ref 2, p.192]

Embrey shows that, when giving uncertainty judgments, respondents do significantly better when dealing with likelihood ratios and odds rather than probabilities. Embrey concludes, "that judges (subject-matter experts) are best at making simple directional judgments of the form 'task A is more likely to be successful than task B' [Ref 28, p 9]." Swain's work supports Embrey's. Swain adds:

> Persons who will not guess at the probability of a particular event will readily rank-order several events in terms of increasing difficulty, hazard, or other dimension, and they will do this ranking with great confidence. [Ref 10, p.101]

Miller and Swain comment, "Humans are very capable of making qualitative judgments along one dimension [Ref 1, p. 238]."

Estimation methods for human error probability that allow a person without probability-estimating skills to relate his expert understanding of error phenomena by simple directional judgments could be very useful. Of the four

expert judgment methods proposed by the NRC, two methods are based upon simple directional judgments: paired comparisons and indirect numerical estimation.

A problem with paired comparisons is the large number of judges required to obtain valid estimates of the task positions on a subjective scale. The relative frequency by which one task is rated more likely to fail than another by a large pool of experts is what leads to a scaled value for that task. If there are only five judges providing input then there are insufficient observations to be significant.

The indirect numerical estimation method of obtaining human error probabilities from expert judgement is a robust procedure and is the primary procedure for estimating human error rates pursued in this thesis. Like paired comparisons, it depends mostly on human qualitative versus quantitative judgments. The indirect numerical estimation method asks the respondent two questions concerning task failure in his area of expertise:

1) Is this task error more or less likely than that task error?

2) How much more or how much less likely is the first task error versus the second task error?

A detailed discussion of the conversion of these expert judgments to human error data by the indirect numerical

estimation method is given by Seaver and Stillwell [Ref 12]. A summary of that process is given in the example below.

Using the one-by-one comparisons given by a respondent, a subjective scale of likelihood is generated. Assume a respondent gives these likelihoods for four mutually exclusive, independent task errors that encompass the entire set of errors that can occur on a given system:

Task A error is twice as likely as Task B error.

Task B error is just as likely as Task C error.

Task C error is three times as likely as Task D error.

The likelihood of task error for all tasks can simply be written in terms of any one task error. In the example, use D as the base scale:

Task A error = 6 X (Task D error)

Task B error = 3 X (Task D error)

Task C error = 3 X (Task D error)

Task D error = 1 X (Task D error)

If the probability of any one task error is known or estimated from some other source (Task D for example) then the probabilities of all four events are known.

If the error probabilities are normalized, then the probability for error in any one task is known, given that an error occurs. Normalization takes place in the example problem:

$$6D + 3D + 3D + 1D = 1.00$$

$$D = .0769$$

Therefore, given an error occurs on the system, the probability that it was:

Task A error is 46%

Task B error is 23%

Task C error is 23%

Task D error is 8%

These probabilities for task error apply to one respondent.

The next topic concerns the number of respondents needed to generate good point estimates of the error data being studied. Von Winterfeldt and Edwards state, "Both theory and evidence teach us to use more than one respondent whenever we can. [Ref 29, p.113)." Guttman and Swain, commenting on the indirect numerical estimation technique, cite the work of Von Holstein in stating, "as with direct numerical estimation, little is gained by using more than six experts [Ref 14, p A-46]." Hogarth writes:

> ...judgments between individuals are likely to be correlated. Thus one is often averaging redundant information with the result that beyond a certain point gains in adding experts to a group are small. It has been estimated that in most predictive situations involving the use of experts there is little point in averaging more than about ten persons and that six or seven will often be sufficient. [Ref 2, p 195]

The next subject is the aggregating of several individual likelihood estimates to a single estimate

applicable to the entire production facility. Many schemes exist for combining several likelihood estimates into a single estimate. Von Winterfeldt and Edwards offers this insight:

> Since proper scoring rules are convex functions on the probability simplex, the score of the average of individual probabilities will necessarily be better than the average of the individual's scores. [Ref 29, p.133]

The authors continue with this straightforward recommendation:

> Simply elicit the desired uncertainty measures from each member individually.... Transform the results into probabilities and average them. The odds seem excellent that, if you do anything more complex, you will simply be wasting your effort. [Ref 29, p.136]

This thesis pursues the method recommended by Von Winterfeldt and Edwards.

4. Consistency in Expert Judgment

Workers and inspectors are typically trained to simply perform the tasks required in their jobs. They are not routinely trained to make quantitative judgments about phenomena relating to their work. When asked to make quantitative judgments it can be expected that some personnel are overwhelmed with the requirement and thus fail to provide valid input. It would be helpful to have a means to screen the incoming data to eliminate surveys of those respondents who were incapable or unwilling to provide valid data.

Consistency on the part of a respondent is some measure of objectivity, internal logic, and operational experience. Saaty defines the term:

> The meaning of consistency is that the intensities of relations among ideas or objects based on a particular criterion justify each other in some logical way. (Ref 17, p 18)

Some measure of consistency is necessary to establish the credibility of the expert whose judgments will eventually affect a final decision. Saaty states, "We do not want the decision to be based on judgments that have such low consistency that they appear random (Ref 17, p.82)." Stillwell and Seaver add, "High levels of inconsistency would suggest the entire judgmental process is suspect (Ref 13, p.32)." A way to identify inconsistent respondents is to require them to make more pairwise ratio judgments than absolutely necessary and then use those judgments to check the respondent's internal consistency. Seaver and Stillwell describe how this works for the indirect numerical estimation method of obtaining human error probabilities:

> To obtain a complete set of probabilities for N events only requires a minimum of N-1 such judgments and an independent estimate of the human error probability of one event. Additional judgments, however, may be obtained as consistency checks. [Ref 12, p A-46]

When more pairwise ratio judgments are made by a respondent than is absolutely necessary there will most likely be some inconsistency. Stillwell and Seaver remind that, "Some inconsistencies enter into all judgmental processes. (Ref 13, p.32)" Saaty argues that some amount of inconsistency is

necessary as humans adapt to an ever-changing world. Saaty states:

> We may not be perfectly consistent, but that is the way we tend to work. It is also the way we grow. When we integrate new experiences into our consciousness, previous relationships may change and some consistency is lost. [Ref 17, p 82]

A level of consistency is desirable to establish respondent validity and expertise. A level of inconsistency, however, is to be expected among human judgment. Saaty comments, "As long as there is enough consistency to maintain coherence among the objects of our experience, the consistency need not be perfect [Ref 17, p.82]." There is a definite need to establish an acceptable level of inconsistency in a judge, beyond which the judgments are discarded as invalid.

To obtain some measure of consistency Saaty suggests the development of an (N X N) reciprocal matrix where N represents the number of items for comparison. A respondent makes a ratio comparison between every two possible items such that a total of (N) X (N-1)/2 judgments are made. The (N X N) matrix is filled in with ones down the main diagonal, the (N) X (N-1)/2 judgments fill the lower triangular matrix below the diagonal of ones, and the reciprocals of the judgments fill the upper triangular matrix above the diagonal of ones.

The maximum eigenvalue (λ_{max}) for this matrix is a measure of consistency of the judgments in the matrix. Saaty

proves that, "A positive reciprocal matrix is consistent if and only if λ_{max} is equal to N. (Ref 16, p.181)" Saaty then turns λ_{max} into a consistency index (CI) by the following operation:

$$(2\text{-}1) \quad [\ \lambda_{max} - N\ ] \ /\ [\ N-1\ ] = CI.$$

Saaty suggests that comparing the CI of a set of respondents' judgments against that CI found by a randomly generated reciprocal matrix should give a general measure of the consistency called the consistency ratio (CR):

$$(2\text{-}2) \quad (\ CI_{respondent}\ ) \ /\ (CI_{random\ matrix}) = CR.$$

The random entries in the random reciprocal matrix are chosen by computer from the range of possible values used by the respondents on their original survey. Several hundred random matrices are computed with respective CIs for each. Those CIs are then averaged to obtain a mean CI for a random matrix. Appendix D shows the table for judgments limited to a one to nine scale and describes the generation of the table in more detail.

Saaty provides a general rule for acceptable consistency ratio values with which he had success in his work. Saaty maintains that a consistency ratio less that 0.1 demonstrates acceptable consistency and that a respondent providing such consistency is giving judgments worth considering in decision-making. [Ref 17, p. 83]

A disadvantage of Saaty's method is the number of judgments required of each respondent. In a 4 X 4 matrix an expert makes only six judgments [(4 X 3) / 2]. In a 10 X 10 matrix an expert must make 45 judgments [(10 X 9) / 2]. Saaty suggests extensive use of hierarchies so that the number of judgments are reduced. For example, if the 10 X 10 matrix could be partitioned to sets of four, three, and three for pairwise ratio comparisons then the number of judgments is reduced from 45 to 15. Figure 1 depicts the reduction of required judgments that is accomplished by use of a hierarchy.

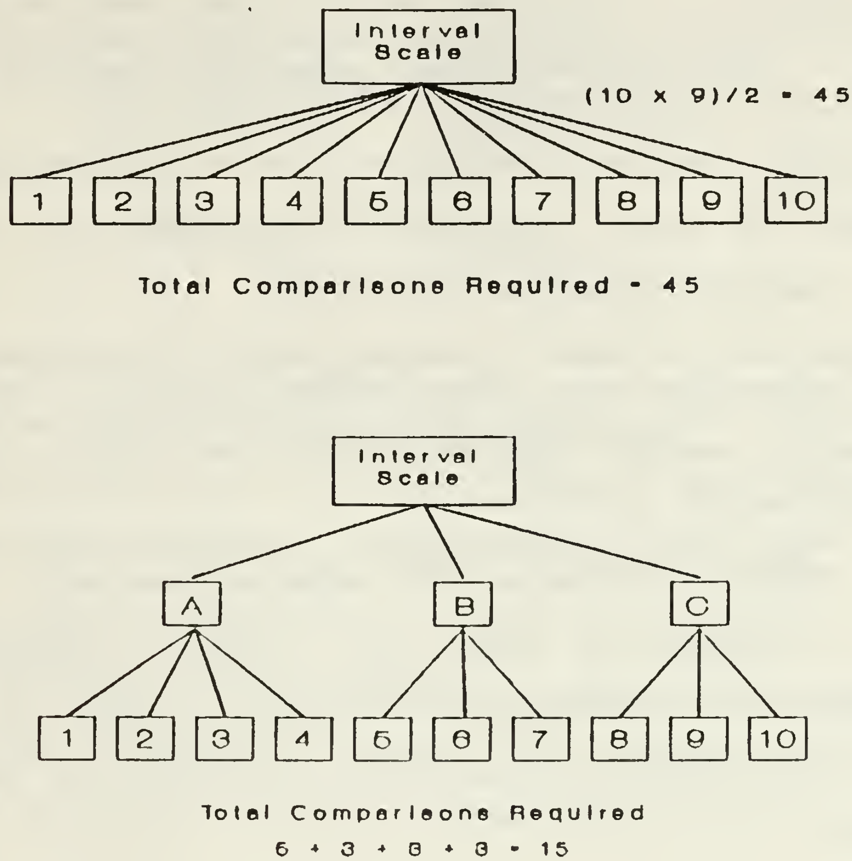
Saaty's method is the method pursued in this thesis for establishing sufficiently consistent input for consideration in decision making.

C. THE PROBABILITY OF INSPECTOR ERROR

1. Inspectors Make Mistakes

Traditionally inspectors are viewed as a panacea for production problems. Many production and quality assurance plans are premised on an assumption of 100% accuracy on the part of inspectors. Inspectors are not perfect. Swain makes this clear,

> There is no point in arguing whether people should make errors. We all do. Human error rates, like material failure rates, are merely facts [Ref 10, p.5].



$$N = (n) \times (n-1)/2$$

where N = number of comparisons needed to establish interval scale using the Pairwise Comparisons Method.

n = number of items to be put in interval scale.

Figure 1 - Reduction of Pairwise Judgments

Drury makes this call to action:

> Intrinsically, man is rarely perfect in either detection or diagnosis. . .This has led in recent years to studies which have demonstrated the effects inspector's errors can have. . .and the need to take account of realistic values of inspector's errors. [Ref 9, p.11]

To decrease the error rate some form of data collection is necessary to make a quantitative assessment of inspector error. Bennett emphasizes this point:

> So what must be done to achieve quality objectives given that inspection error is to be ever present? The answer is simple. The quality control engineer must be able to accurately measure these errors and then be able to design for them. [Ref 9, p.1]

2. The Direct Relationship: the More Time Inspector Takes, the Greater the Inspector Accuracy

An appealing method for viewing inspector error probability was introduced by Wreathall in work for the NRC. Wreathall's Operator-Action Tree method (OAT) is depicted in Figure 2.

> The OAT approach is based on the assumption that human response to an environmental event consists of three activities:
>
> 1) perception,
>
> 2) diagnosis, and
>
> 3) response.
>
> The basic operator-action tree is based on the potential for error in each of the three activities.
>
> The second major assumption is that time available for diagnosis is the dominant factor determining the probability for failure. That is, given a short period of time, people will fail to diagnose a situation

correctly more often than when given a longer period. [Ref 1, p.236]

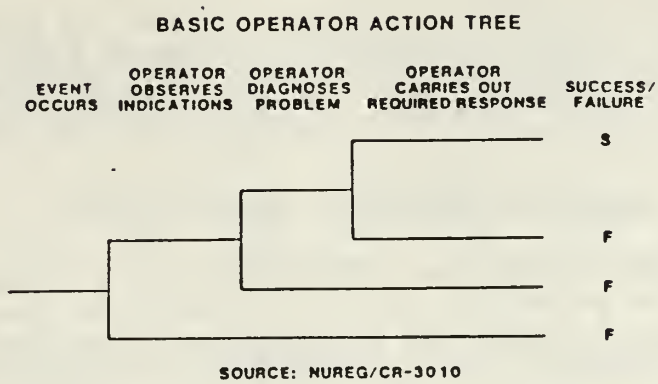


Figure 2 - Operator-Action Tree

The intuitive appeal for the first assumption is overwhelming. An inspector must "see", or visually fixate, on the event. He must be trained sufficiently to be able to discriminate error in the object of his fixation. Finally, the inspector must be able to respond properly to overcome the error. Failure to accomplish any one of these three steps will result in inspector failure on the task.

Not only does the second assumption, that less time available means more inspector errors, make intuitive sense, but there is strong experimental basis for it. Drury's work with flat glass inspectors [Ref 26, p.265], Buck's experiments with Landolt rings [Ref 9, p.169], and Rizzi's tests with flawed dot patterns on cards [Ref 25, p.279] convincingly demonstrate that inspector errors increase with less exposure

time to the object being inspected. Drury summed up his work and that of Smith and Barany [Ref 22] when he wrote:

> In all of the studies, a similar effect is observed, in that as more time is allowed to inspect each item, the probability of rejecting a faulty item increases whilst the probability of accepting a good item decreases. [Ref 32, p. 6]

Drury suggests something akin to OAT:

> The inspection mechanism postulated is a visual search until either a potential defect is found or time runs out for that item, followed by a decision about the potential defect as to whether it is acceptable or rejectable. [Ref 32, p. 6]

Just as the OAT method suggests, a visual search must take place until the inspector "sees" the prospective error. This success of the visual search is no doubt a function of many factors. The experimental evidence reviewed points strongly to time available to the inspector as the most significant factor to whether the search will be successful or not. If the search leads to a prospective error then the inspector must decide whether to accept or reject the object bearing the prospective error. This decision involves experience of the inspector, remaining time available to the inspector, and costs and payoffs relating to finding errors.

Smith and Barany found signal detection theory helpful in describing the decision an inspector must make [Ref 22, p.300]. Drury also used signal detection theory to model inspector decision performance [Ref 32, p.2-6]. Chapman and

Sinclair give this opinion of the application of signal detection theory to their study of inspection work:

> Perhaps the most important thing to emerge from this study is the usefulness of the theory of signal detection in industrial inspection situations both from a theoretical and a practical point of view. The theoretical value lies in the insights it provides into an inspection task, and the practical value arises from the fact that it allows economic justification for the application of ergonomics to inspection, and the rel-ative ease with which recommendations for improvement can be derived. [Ref 9, p. 241]

The basics of signal detection theory were established by the pioneering work of Tanner, Swets, Birdsall, and Green between 1954 and 1966 [Ref 8, p.18]. Figure 3 is the common depiction of the theory applied to the inspector's decision [Ref 9, p.14]. The detection of signals is assumed by the theory to involve two processes: discrimination (d') and decision (β). Discrimination (d') requires the inspector to be capable of distinguishing between success and error on a task he is inspecting.

Discrimination is affected by such things as the experience of the inspector (more experience tends to make d' larger) and the time available to perform the inspection (more time tends to make d' larger). Decision (β) requires the inspector to accept or reject what he sees. A decision (where the point β is between the two modal values of the Gaussian curves) is influenced by such things as the inspector's

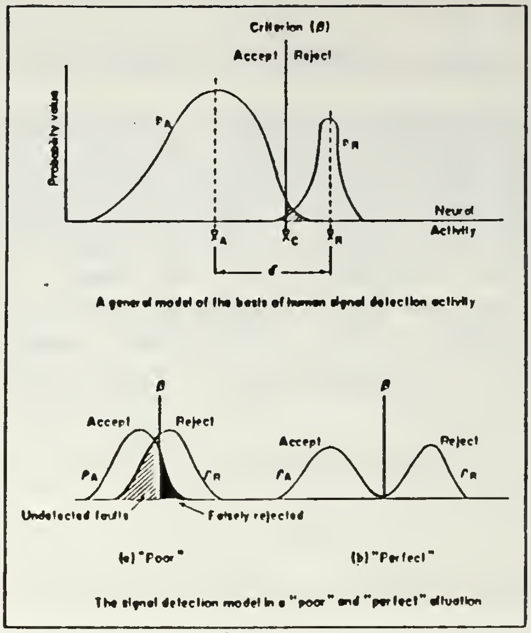


Figure 3 - Signal Detection Theory [Ref 9, p.14]

subjective probability that an error will occur (if he thinks errors are very likely then he is more likely to reject) and his attitude toward risk. [Ref 8, p.18-21]

Smith and Barany explain in terms of signal detection theory what transpires to cause a reduction in inspector accuracy with a decrease in time available. Smith and Barany write:

> If the pace of the inspection task is increased, then the inspector will have less time in which to make his observation, and his observing mode will tend toward that described as "blurred observing".[Ref 22, p.300]

The effect of "blurred observing" is to decrease discriminability (d'). With discriminability (d') reduced there is more overlap of the two Gaussian curves (see Figure 3) and whatever decision (β) is made must result in either

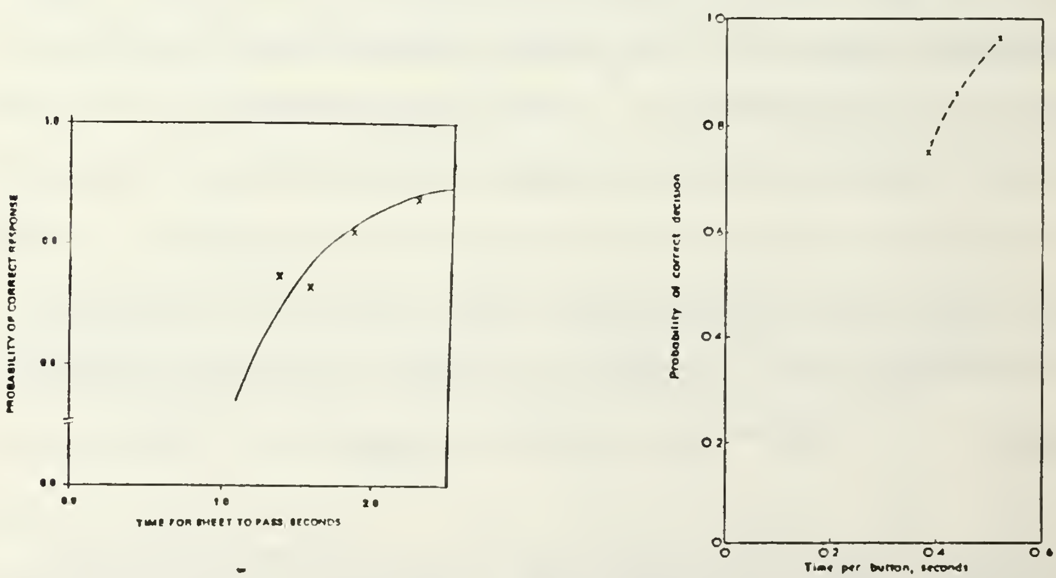
more Type I or Type II errors. Smith and Barany conducted experiments which demonstrated what signal detection theory postulated.

The experimental results from Drury [Ref 26]; Rizzi, Buck, and Anderson [Ref 25]; and Smith and Barany [Ref 22] noted above are for relatively simple inspection tasks along one dimension (flaws in sheet glass, numbers of holes in disks, dots on cards) as opposed to more complex tasks with a multitude of possible errors on several dimensions (circuit boards, silicon chips). For simple inspection tasks the experimental results clearly show a direct relationship between inspector time to observe and inspector accuracy. Schoonard emphasized this point with an experiment where seven different classes of errors were possible on circuit boards. The inspection tasks for the seven classes were ranked from simplest to most difficult. A deliberate slowing of the inspection time resulted in marked improvement on the more simple inspection tasks but not so great an improvement on the other, more difficult inspection tasks. [Ref 24, p. 368-376] Drury predicted this finding by signal detection theory principles. In reference to simple inspection tasks Drury wrote,

> For simple discriminations (such as the Smith and Barany experiments) the discriminability will be high enough to give almost perfect inspection as the time allowed is increased. [Ref 32, p.7]

It is clear from experimental results that simple inspection task accuracy improves with time.

The nature of the relationship between time taken by inspector and his accuracy was explored by both Rizzi, Buck, and Anderson [Ref 25, p. 279] and Drury [Ref 26, p.265]. Drury found an exponential relationship between the cumulative probability of locating a flaw in sheet glass and time taken to inspect. Rizzi, Buck, and Anderson conducted tests on subjects inspecting small cards with dots. Similar to Drury's results, Rizzi, Buck, and Anderson also found the inspector's exposure time to the object exerted an exponential effect on the probability of a correct detection. Figure 4 shows the results of Drury's and Smith and Barany's work with the effect of time on the probability of inspector accuracy.



Drury [Ref 26, p.264]   Smith and Barany [Ref 32, p.5]

Figure 4 - Inspector Accuracy as a Function of Time

3. Limits to the Direct Relationship

It would seem that there must be some limit to the direct relationship that more time spent by an inspector yields more inspector accuracy. This section reviews experimental results that confirm both lower and upper bounds to this direct relationship.

a. Minimum Time is Limited by Time Required for Visual Fixation

The lower bound for this direct relationship is the physical limitation of the human eye to focus and fixate on any visual stimuli and the brain to comprehend what the eye is seeing. Experimental results revealing what might be a minimum time for the eye to fixate and the brain to begin to function for inspection purposes are offered by Drury. Drury concluded from his experimental results that it took seven tenths of a second (700 milliseconds) for his subjects to open and focus their eyes and begin searching for errors. [Ref 26, p. 260]. During that initial time from zero to seven tenths of a second there is no increase in inspector accuracy.

b. Maximum Time is Limited by Human Vigilance

The upper bound for the direct relationship of more time resulting in more accuracy is the result of decreased vigilance that occurs when an inspector exceeds his attention span. Chapman and Sinclair [Ref 9], Kochhar and

Jaisingh [Ref 23], and Schoonard, Gould, and Miller [Ref 24] demonstrated upper bounds to the direct relationship that was found by Drury [Ref 26]; Rizzi, Buck, and Anderson [Ref 25]; and Smith and Barany [Ref 22]. Experiments by Chapman and Sinclair of experienced personnel inspecting poultry carcasses at a meat processing plant [Ref 9, p.231] and the work of Kochhar and Jaisingh with experienced inspectors checking products on a CRT screen [Ref 23, p. 44] are two examples of note. Both showed initial improvement in inspector accuracy as time was increased, just as Drury and others had noted. At a point, however, Chapman and Sinclair [Ref 9] and Kochhar and Jaisingh [Ref 23] reported a degradation in inspector accuracy when inspectors were made to take more time in their visual inspection tasks. Schoonard, Gould, and Miller reported similar findings with their experienced inspectors who were checking circuit boards for any of seven different classes of errors that might be present. As Schoonard, Gould, and Miller increased the inspection time to 1.5 times the standard time the inspectors spent on their tasks, significant improvement resulted across all seven classes of error-types. With any additional increases over the 1.5 times the standard time for the inspectors, there was no improvement in inspector accuracy. [Ref 24, p.365]. Chapman and Sinclair offer a possible explanation for this degradation phenomenon with

increase in inspector time:

> ...during the course of such a task periods of inattention occur which become more frequent or prolonged as presentation time increases.... A possible answer (for the prolonged periods of inattention) may be that the human organism maintains a homeostatic level of arousal, and if this is dependent on incoming stimuli, it could be argued that at the lower speeds additional stimuli are required which are obtained during the extended periods of inattention to the task. [Ref 9, p 249]

Kochhar and Jaisingh offer this explanation of the decline in inspector accuracy resulting from increased inspection time available that was noted in their experiments:

> Error detection in vigilance situations of this type is dependent upon operator arousal levels. Thus the low levels of fault information and product pacing did not arouse the subject to the point where performance could be optimal.... It could be inferred that operator performance in inspection is related to arousal and in evaluating trade-offs between the different variables due consideration should be given to maintaining operator arousal. [Ref 23, p. 44]

The phenomenon that more time beyond a certain critical point does not yield more inspector accuracy is real. Analysts cannot blindly assume that more inspector time will continue to yield an improving probability for accuracy. To continue to allot more inspector time is counterproductive. In addition to an actual decrease in inspector accuracy, more inspector time costs the facility either the salary of more inspectors or reduced productivity due to a slowed production line.

4. Significance of Schoonard's Findings

Many visual inspection experiments have been conducted. Few of those experimental findings have direct application to the actual inspection operations on production lines. Schoonard, Gould, and Miller explain the shortcomings of the bulk of visual inspection experiments:

> Fundamental laboratory studies... have limited application to most actual inspection situations because they use discrete targets on homogenous backgrounds, whereas most inspection situations consist of poorly defined targets on non-homogenous backgrounds. [Ref 24, p 365]

Another shortcoming of much experimental work is the hiring of students to perform the simple visual inspection tasks in the laboratory studies. The nature of most actual inspection tasks is sufficiently technical to require specially trained inspectors. The inspectors' frames of mind, motivation, and dedication have much to do with how they will perform when inspecting. The results will very likely differ significantly between experiments where fully paid and trained inspectors perform technical inspection tasks that they perform everyday and other experiments where students are paid some nominal fee to perform very simplistic visual inspection tasks for a day. To extrapolate information from experimental work for use in analysis of actual inspection work, the experiment should closely resemble the actual inspection situation in several key respects.

5. Estimating Time for Inspector to Inspect

An estimate on the standard time that it takes an inspector to perform a visual inspection task is necessary to establish the range of time over which an inspector can productively be employed on a task. In regards to eliciting estimates of times required to inspect for worker error the NRC writes:

> Estimation of performance times poses a more difficult problem (than human error probabilities). The best approach is to take measurements of actual or simulated task times. A second-best approach is to combine estimates of those who perform the tasks. [Ref 14, p. 6-1]

Nothing precludes empirical measurement to derive the required time estimates of visual inspection tasks except the cost and difficulty of doing so. There may be several potential worker errors within the visual scope of the inspector at any one time. Measuring the time an inspector takes on any one visual task is complicated by the difficulty of the experimenter trying to track where the inspector's eyes are fixated. The costs of empirical measurement of times for visual inspection tasks is large due to the fact that each facility must likely derive its own time estimates due to individual facility peculiarities. Those peculiarities involve, for instance, level of training of the inspectors, special equipment that inspectors use, and standard operating procedures within the facility.

An alternative to empirical observation to derive time estimates on inspectors is a modification of the indirect numerical estimation technique. The standard inspector time on one task may be known through empirical observation. All other tasks are compared to one another on a respondent survey form. The respondents make directional judgments between pairs of tasks that appear on the survey form. The judgments call for:

1) Which of the two visual inspection tasks requires more time to accomplish?

2) About how much longer (in terms of seconds) does the one task take to inspect compared to the other task?

Through simple algebraic manipulation estimates are derived from the survey as to the amount of time taken to perform all visual inspection tasks. This algebraic manipulation is given with sample data in Appendix C. These point estimates are averaged with the input of others from the same facility to yield a facility-wide estimate of time for an inspector to visually inspect every task.

D. THE COSTS OF ERROR

Many costs vie for the attention of the analyst and the executive. Swain writes;

> Most consideration must be given to those potential errors with an intolerable combined possibility of occurring, going undetected, and causing an unacceptable system consequence. [Ref 10, p.90]

An error that causes unacceptable system consequence is an error which is potentially too costly in terms of the consequences of interest for the system. Swain writes of the difference between errors that cause acceptable system consequence and those that cause unacceptable system consequence:

> For some errors, the system consequences may not be severe and perhaps a somewhat high possibility of an uncaught error can be tolerated. Other potential errors might have such severe consequences that uncaught error probabilities of even one in a million could not be tolerated. For example, a pharmaceutical company could probably not tolerate the existence of one cyanide capsule in one million multivitamin capsules delivered to the public. [Ref 10, p.89]

The analyst must develop ways to assess potential costs of errors so that the manager can allocate error catching resources with regard to the potentially most damaging errors.

The reallocation of error-catching resources in an organization is a change in system design. It is important to remember that in a systems approach:

> ...successful design changes may not always reduce the probability of an error-but they will reduce the probability of undesirable system effects due to such errors. [Ref 10, p 90]

In the multivitamin example mentioned by Swain, a very successful design change may be one that increases the incidence of cracked capsules (a frequent error of small costs) in bottles, but absolutely assures that a cyanide capsule (a rare error of monumental costs) never shows up in

a bottle of multivitamin capsules. It is essential that the potential costs of errors be estimated before resources can be allocated to reduce the probability of undesirable system effects.

For any one type of error there is a corresponding distribution of costs. The U.S. Army suggests a quick method for establishing a cost distribution based on the Project Evaluating and Review Technique (PERT):

> One might well consider the possible use of subjective cost estimates based on PERT...
>
> Once it has been decided to employ the PERT technique to determine likely costs, it becomes necessary to estimate the most optimistic cost, the most pessimistic cost, and the most likely cost...
>
> These concepts fit in rather well with the idea of a generalized Beta distribution. An adequate statistical model of the Beta density to represent probable cost is:
>
> (2-3) $$f(c) = k(c - A)^p * (B-c)^q, \quad A<<<B$$

where:

$f(c)$ = probability density function of costs

c = cost

k = constant to make area under distribution curve = 1

(2-4) $$k = 1 / [(B-A)^{p+q+1} * \beta(p+1,q+1)]$$

β = complete Beta function

A = minimum cost

B = maximum cost

p,q = parameters determining the shape of the beta distribution [Ref 33, p.36-6]

From the PERT cost distribution a mean and standard deviation can be easily computed.

(2-5) m = estimate of mean cost = $(a + 4*m_o + b) / 6$

(2-6) v = estimate of variance = $(b - a)^2 / 36$

where:

a = estimate of minimum cost

b = estimate of maximum cost

m_o = estimate of most likely cost
[Ref 33, p.36-7]

See Appendix B for more details of this procedure.

The PERT cost estimation technique requires expert opinion to generate estimates for the cost distribution. Moder and Phillips point to an immediate supervisor as one capable of providing estimates for PERT:

> The basis of PERT computations...depends on the judgment of the person in charge of the activity in question. He is asked to call on his general experience, and his knowledge of the requirements of the activity in question, to consider the personnel and facilities available to him, and then to estimate the three (costs): optimistic, pessimistic, and most likely (costs). [Ref 34, p 204]

E. GOAL PROGRAMMING

1. Versatility and Utility

Goal programming is a powerful mathematical programming technique which allows for models that very closely approximate problems in industry, business, and government. The power of goal programming is wrapped up in

its ability to overcome human analytical weaknesses. Paulos writes about one of those weaknesses:

> There's a strong human tendency to want everything, and to deny that trade-offs are usually necessary...Trade-offs between...speed and thoroughness...are frequently muddled and covered with a misty gauze, and this decline in clarity is usually an added cost for everyone. [Ref 7, p.131]

The decision maker can often visualize and announce what he wants to accomplish in several competing areas. The level at which the decision maker wants to achieve is a goal. The several goals that a decision maker has are often very different. Budnick, Mojena, and Vollman write of the power of goal programming:

> Goal programming...allows for consideration of multiple goals. The goals may or may not be of the same dimension or unit of measurement. In addition, goal programming allows for consideration of conflicting goals. [Ref 6, p 352]

When it comes to giving something up for something else the decision maker often balks. Bell, Keeney, and Raiffa note the quandary in which the decision maker finds himself:

> This is what the multi-objective problem is all about: the making of vexing value trade-offs. There is no magic formula for making these value trade-offs. The decision maker would, of course, like to do the best he can in each attribute, but it is not possible to maximize several things at once. If we reduce unemployment, it may be at the expense of increasing inflation... These problems are pervasive and are at the heart of many public policy controversies. [Ref 35, p.4]

Any method that helps coax the decision maker into making tradeoffs is a help. Goal programming is a method for attacking the multi-objective problem.

A decision variable is established which is the entity over which the decision maker has some control or influence. The decision variable is often a resource. The amount of the resource that can be employed is limited by constraints on the system. Through some known or hypothesized relationships varying amounts of the decision variable effect the levels of goal achievement. The relationships by which those decision variables affect the decision maker's goals are captured by mathematical models in the goal constraints. An achievement function mathematically combines the deviations from all goals. By minimizing or maximizing the achievement function through linear or nonlinear programming methods a level of resource (decision variable) use is determined such that the goals are most closely achieved.

Goal programming calls for the satisfying of goals rather than the maximization of some single objective, as is often the case in standard linear programming. The decision maker states his goals, ranks them as to their importance, and weights them if necessary. The analyst determines the relationships between a controllable variable and the achievement of the goals. Goal programming gives the amount

of the controllable variable to expend to accomplish as closely as possible what the decision maker desires.

Budnick, Mojena, and Vollman explain the satisfying of goals in this way:

> With multiple goals, all goals usually cannot be realized exactly. Goal programming attempts to minimize the deviations from these goals with consideration given to the hierarchy of stated priorities. [Ref 6, p 352]

Ignizio refers to the greater applicability of multi-objective models to actual problems as a reason to pursue goal programming. Hillier and Lieberman present a concise review of goal programming [Ref 5, p 242-252].

2. Applied to Allocation of Inspection Time

The overall allocation of inspection resources problem is one that is determined by executives in an organization. Take, for instance, an organization making an investment decision. A million dollar budget for quality assurance is being allocated. The decision of going with twenty visual inspectors or two visual inspectors and robotics is a decision far removed from the floor manager. It is not commonly within the manager's means to hire or fire inspectors or buy new inspection-aiding equipment. The manager must take what the organization provides him, whether it is two or twenty visual inspectors, and make the facility work to achieve quality and quantity standards. Basically, the only thing that the floor

manager may directly control in regard to inspection of the final product is the allocation of time that the inspector spends per visual task.

a. **Decision Variables**

The decision variables in goal programming are the variables over which the decision maker has some control and which have some influence over the achievement of the goals. In goal programming to achieve allocation of visual inspection resources the inspector time spent on checking the work of others is the decision variable (X_i, i= the number of visual inspection tasks). The purpose of goal programming is to determine an acceptable use of the decision variable.

b. **System Constraints**

A system is always limited in the amount of the decision variable that can be employed. This limitation is due to a limited supply of the resource or limited capacity of the system to employ the resource. In goal programming to allocate visual inspection time resources at least two system constraints exist: the minimum and the maximum amounts of time that can be spent productively on each of the inspection tasks. These limits are based on the experimental findings of Drury [Ref 26] and Schoonard, Gould, and Miller [Ref 24].

c. Goal Constraints

Goals reflect the objectives of the decision maker. With visual inspection there is usually a thoroughness goal and a speed goal that the manager specifies. These goals are elastic, allowing some deviation if insufficient resources are available to satisfy both goals.

$$(2\text{-}7) \quad \sum_{i=1}^{m} X_i - TPOS + TNEG = TIMEGOAL$$

where m = the number of inspection tasks to be done. The right hand side of this constraint represents a goal in terms of time in which the manager wants inspections to be completed. The deviation from the goal which matters to the manager is captured by TPOS.

$$(2\text{-}8) \quad \sum_{i=1}^{m} [\, f(x_i) * C(error_i) \,] - ACCPOS + ACCNEG = ACCGOAL$$

where $f(x_i)$ = probability of inspector error as a function of time he spends on the inspection task,

$C(error_i)$ = the cost of $error_i$ in meters.

The right hand side of this constraint represents a goal in terms of accuracy that the manager wants to be met. The deviation from the goal which matters to the manager is captured by ACCPOS. Deviations in one goal versus another are

encouraged through weights that are applied to the respective deviations in the achievement function.

The desires of the decision maker are often preemptive: one tier of goals must be satisfied before another tier can be considered. Hillier and Lieberman describe preemptive goal programming and the handling of goals:

> Consider the case for preemptive goal programming. Such a case arises when one or more of the goals clearly is far more important than the others. Thus the initial focus should be on achieving as closely as possible these first priority goals. After we find an optimal solution with respect to the first priority goals, we can break any ties for the optimal solution by considering second priority goals. When we deal with goals on the same priority level, our approach is just like the one described for nonpreemptive goal programming. [Ref 5, p.245]

Assume a number of independent visual inspection tasks which must be accomplished properly for an error-free product to come out of the facility. Assume that a cost, a quantitative measure relating to loss of customer satisfaction, can be associated with each error on a product that leaves the facility. If the manager can state a maximum tolerance cost, within which the confidence of the consumer is maintained, then the building of tiers can proceed in a manner such as this:

TIER 1.

Any inspection task covering a worker error which has a cost greater than the maximum tolerance cost should be considered first to maintain the consumer's confidence.

TIER 2.

> If any time remains after the first tier inspection tasks are allotted their time then that remaining time can be applied to the second tier of goals. The second tier consists of any visual inspection tasks not addressed in tier one.

If there is insufficient time to cover all tasks in the first tier, then goal programming is invoked to determine the allocation of time across those first tier visual inspection tasks. If sufficient time exists for the first tier tasks to receive maximum time then they are given their full allotment of time and goal programming is invoked to allocate time on the visual tasks in the second tier.

d. Achievement Function

The achievement function takes the goals within one tier of the goal program and considers the deviations from each goal simultaneously. The deviations from goals are given weights by the decision maker in accordance with their relative importance to the organization.

In the goal program for allocating visual inspection resources, the decision maker gives a weight to the time goal deviation and the accuracy goal deviation. The appropriate weight is multiplied by the deviation variable for each goal. The two weighted values are then summed to equal a total deviation for the problem. The achievement function minimizes this total deviation value. As the goal program

iterates, it trades off accuracy for time or time for accuracy until a solution is reached which best satisfies the two goals in light of their respective weights.

The standard achievement function for allocating visual inspection time is given in Equation 2-9.

(2-9) Minimize DEVIATION

where DEVIATION = (TIMEWT * TPOS) + (ACCWT * ACCPOS)

e. The Formulation

The generic goal program to accomplish allocation of inspection time is shown in Figure 5.

Achievement Function

Minimize:

DEVIATION = (TIMEWT * TPOS) + (ACCWT * ACCPOS).

Goal Constraints

Subject to:

$$\sum_{i=1}^{m} X_i - TPOS + TNEG = TIMEGOAL$$

$$\sum_{i=1}^{m} [\, f(x_i) * C(error_i) \,] - ACCPOS + ACCNEG = ACCGOAL$$

where m = the number of inspection tasks to be done.

System Constraints

$$T_{MINi} \leq X_i \leq T_{MAXi}, \quad \text{for } i = 1, 2, \ldots, m$$

$$X_1, \ldots, X_m, TPOS, TNEG, ACCPOS, ACCNEG \geq 0.$$

Figure 5 - Goal Program Formulation

F. SOFTWARE SUPPORT OF METHODOLOGY

Suggested software support of the proposed methodology includes computer packages that swiftly perform a number of matrix operations and optimization.

1. Matrix Operations

A means to manage matrix operations is needed to transform the survey responses on worker error into useable data for the model. Some survey responses will be invalid due to internal inconsistencies. As discussed in Chapter II, B-4, eigenvalues are needed to determine the internal consistency in a group of judgments from a respondent. An eigenvalue solver or software which will allow the analyst to manipulate matrices to derive eigenvalues is necessary to permit a timely decision of whether to incorporate various respondent surveys into the model.

A Programming Language (commonly known as APL) is a software product that permits easy manipulation of matrices. The eigenvalue solver that accompanies most APL software packages is used on the illustrative problem of this thesis. APL is used in both Appendix A and Appendix D to derive the eigenvector from respondent surveys for the probabilities of crew error and to derive the maximum eigenvalue to determine respondent consistency.

2. An Optimizing Package

A linear or nonlinear programming package is needed to optimize the objective function. There are 13 decision variables that simultaneously need to be considered.

a. Nonlinear Programming Package

A nonlinear programming package will permit a straight-forward solution to the model. Data which show the increase in inspector accuracy as a function of time is extracted from experimental studies which closely approximates the type of visual task being modeled. A curve fit is made to that data and a function is generated that approximates the curve fit. That function, if convex, can be included directly into the goal constraints for use by goal programming. The curves in all studies indicated in this thesis have indeed been convex.

In the illustrative problem which accompanies this thesis the versatile and powerful Generalized Algebraic Modeling System (GAMS) package is used. GAMS allows for nonlinear programming. An example of the input and output which is produced with GAMS is shown in Appendix E.

b. Linear Programming Package

A linear programming package will permit a solution to the model. There is a minor degree of difficulty

in that the continuous curve generated by the curve fit in nonlinear programming must be broken up and made piecewise linear so that a linear programming package can solve the problem.

The remainder of this thesis is the presentation of a problem to illustrate the methodology of allocating visual inspection resources in a production facility suggested in Chapter 2.

III. BACKGROUND TO AN ARTILLERY PROBLEM

A. THE ARTILLERY ORGANIZATION

The artillery fire support system consists of separate components which contribute to the goals of "rapid and accurate" fires. Depicted in Figure 6 are the components of the artillery system.

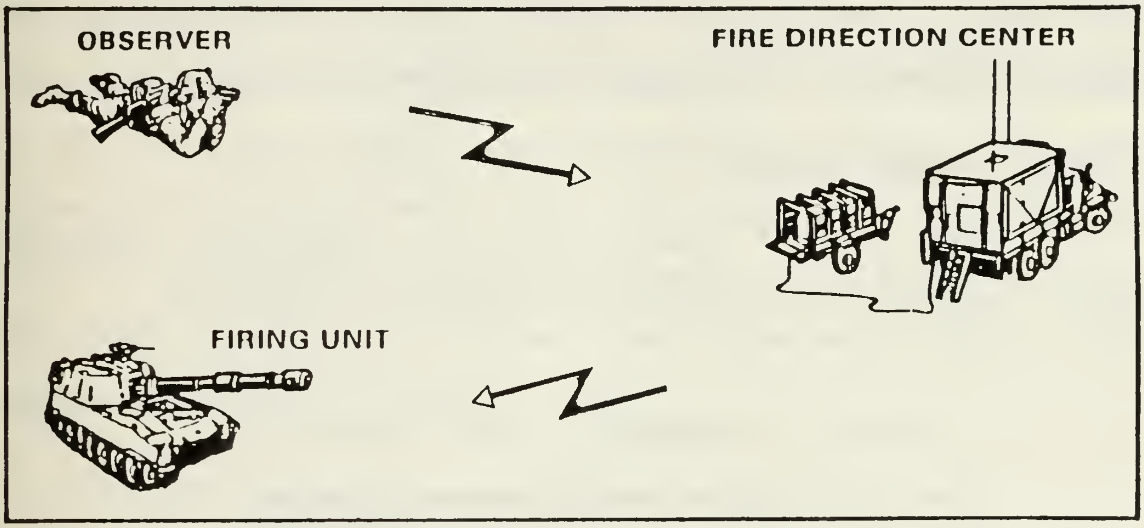


Figure 6 - The Sub-system Components of the Artillery

The observer, a Forward Observer (FO) or a RADAR section, spots a target. The Fire Direction Center (FDC) receives the target location information from the observer and translates that input into orienting data for the guns. The gun section prepares the ammunition, orients the weapon, and fires at the observer's target. Survey sections and meteorology sections support the gun section by giving topological surveyed grid

control and atmospheric meteorological information input into the system.

The system components noted above are grouped into artillery organizations. Several gun sections and one FDC constitute a battery of artillery, commanded by a captain. Several batteries of artillery, observers, and surveyors are organized into a battalion of artillery, commanded by a lieutenant colonel. Several battalions and meteorologists compose a brigade of artillery, commanded by a colonel.

B. ROLES OF THE PLAYERS.

The focus of this thesis is the Gun Section. The Gun Section consists of the members depicted in Table 1.

TABLE 1. MEMBERS OF A GUN SECTION

position	rank	number	yrs in service
Chief	E-6	1	5 - 15
Gunner	E-5	1	2 - 10
Asst gunner	E-4	1	1 - 8
Ammo handlers	E-1,4	3-7	0 - 8

The ammunition handlers prepare the shell that carries the munitions to the target, set the fuze that activates the shell at the appropriate point in its trajectory, and select the propellant charge that propels the shell out of the cannon and towards the target with the proper velocity. The assistant

gunner vertically orients the weapon tube to a designated position so as to obtain the trajectory needed to reach the range of the target. The gunner horizontally orients the weapon to a designated position to place the weapon tube on line with the target. The chief inspects the work of his subordinates to insure accuracy of settings and then commands the crew to fire the weapon.

The FDC computes six elements of data that, when taken together, constitute the weapon aimpoint. Those six elements of data are the horizontal orientation setting, vertical orientation setting, shell type, fuze type, fuze setting, and amount of propellant. Firing the weapon at an aimpoint other than that directed by FDC is a gun crew error and is the responsibility of the chief.

C. POSSIBLE ERRORS THAT A GUN CREW MAKES

The four errors associated with the ammunition handlers are:

1) improperly selecting the shell type,
2) improperly selecting the fuze type,
3) improper setting of the fuze, and
4) improperly cutting the amount of propellant.

The four errors associated with the assistant gunner and the vertical orientation of the weapon are:

1) improperly setting the pre-designated four digit elevation number on the elevation counter,

2) improperly leveling the pitch bubble,

3) improperly leveling the cross level bubble, and

4) failing to have the proper two digit number in the piece correction window.

Figure 7 shows the location of these four errors on the assistant gunner's mount of a towed howitzer. The four errors associated with the gunner and the horizontal orientation of the weapon are:

1) improperly setting the pre-designated four digit number on the deflection counter,

2) improperly leveling the sight mount bubbles,

3) failing to have the proper two digit number in the piece correction window, and

4) not traversing the weapon to acquire a proper sight picture through the panoramic telescope onto the aiming reference point.

Figure 7 shows the location of these four errors on the gunner's mount of a towed howitzer.

In addition to the above twelve errors that a chief must check prior to firing his weapon, there are checks he must make regarding the firing data his crew receives from the FDC. When firing into a clearly defined area for a prolonged period of time a chief is given a schematic that depicts the limits of the area into which he can safely fire. The schematic that depicts the limits for the safe fire of a weapon is called a "safety T". The chief is required to check that the·settings

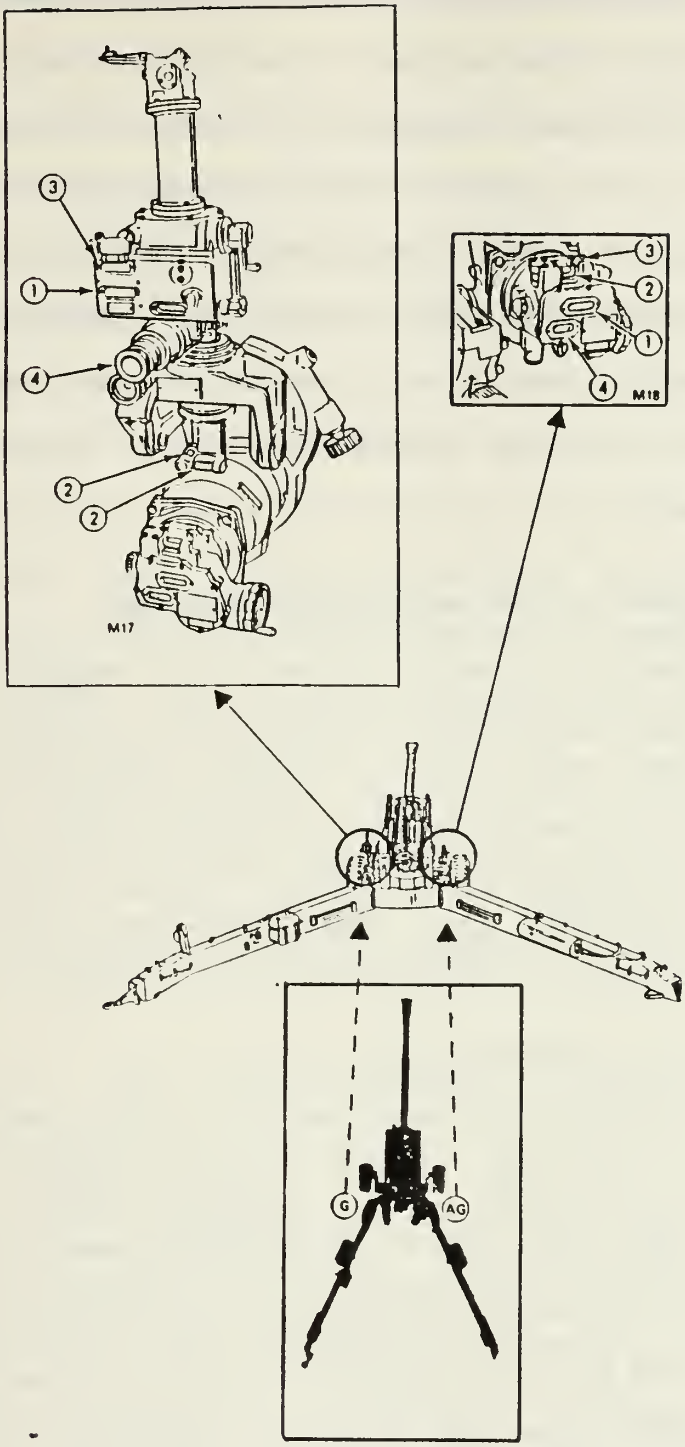


Figure 7 - Potential Gunner and Assistant Gunner Errors

being made by his crew are within the horizontal orientation limits, vertical orientation limits, fuze setting limits, propellant limits, and ammunition constraints imposed by the schematic. In this way the chief insures that crewmen have not set grossly inaccurate data due to garbled communication from the FDC or from fellow crew members. As a minimum, the chief insures by means of the "safety T" that the round his section fires will fall within the limits of safe fire for munitions impact.

D. THE GUN CHIEF'S TIME ALLOCATION PROBLEM

The artillery's primary mission is to support the ground gaining maneuver forces with firepower to destroy the enemy or diminish his will to fight. The artillery accomplishes this mission by providing fast and accurate fires when called upon to do so [Ref.43 p.13]. Each component of the artillery fire support system is called on to contribute to the twin goals of fast and accurate fire.

General Otis states, "(Artillery is) a widespread organism whose ultimate function is to deliver massive firepower exactly when and where the force commander wants it [Ref 30, p 29]." Fast and accurate artillery fire is what the maneuver force demands and what the artillery force must deliver. This thesis recognizes fast and accurate artillery fires as the preeminent consequences of interest (or measures of

effectiveness) for the entire artillery system. The final component, the gun section, shoots the projectile at the target. The crew of men that operate the gun is the focus of the illustrative problem of this thesis.

The primary resources available during fire missions that directly influence gun crew firing accuracy are the gun chiefs. The commander employs the gun chiefs as his personal quality assurance inspectors [Ref 31, p.3-5]. These personnel effect accuracy by inspecting for gun crew errors prior to the firing of each round. There are sixteen distinct, mutually exclusive errors noted previously that the crew can make when firing the weapon. The limited resource that the inspector expends to influence accuracy is the time that he takes to inspect for errors. The inspector's time is limited because artillery fires must not only be accurate, but fast. Excessive time by the inspector detracts from promptness of fires.

Current U.S. Army literature does not specify a method by which an inspector is to allocate his pre-fire inspection time. It is expected that a gun chief will use his artillery experience, knowledge of his crew, and intuition to decide where his time will best be spent between the various error-prone tasks he must cover. Intuition is inadequate in complex decision making, and this problem requires a complex decision

[Ref 3, p.17]. Systems analysis and logic dictate the spending of limited error-stopping resources commensurate with the importance of the error.

This illustrative problem presents an allocation of inspection time model for use by a commander. The model quickly and efficiently analyzes the importance of gun crew errors for an artillery unit by using subjective input from unit leaders garnered by means of surveys. The model then uses goal programming and suggests an allocation of pre-fire inspection time to reduce the probability of undesirable consequences due to errors.

The alternative to allocation of resources by modeling is strict intuition. If intuition is failing in a unit as an effective means of allocating time then modeling offers an alternative. The alternative to modeling by means other than the quick techniques of the methodology in this thesis is to model using input from empirical observations. The use of empirical observations to generate error data is not viable.

The error data needed are functions of training, experience, readiness, and type of cannon weapon system in the unit. These factors vary considerably between units. Consequently, information gleaned in one unit will have little use in another unit. The first three factors; training, experience, and readiness; can change considerably within the

same unit in a matter of weeks. Therefore, information gleaned in a unit may have little use in the same unit the following month. Gathering of unit error data through empirical observation for every artillery unit at frequent intervals is impractical, if not impossible. The modeling methodology must be as efficient as the situation is dynamic. The methodology presented in this thesis is useable by artillery units to allocate inspection time.

E. ASSUMPTIONS

Assumptions in this problem are in two categories. One set of assumptions isolates the effects of errors by the crew so that other off-setting or magnifying errors do not interfere with the analysis of the crew. The second set of assumptions facilitates modeling.

1. Assumptions to Isolate the Problem

The concern of this illustrative problem is the difference between the FDC's aimpoint (the target location) and the gun section's aimpoint (the expected location of shell impact). That difference is the net effect of the error that the gun crew makes and the chief fails to catch. This error is measurable in terms of the number of meters by which the shell is expected to miss the target.

To isolate the gun section regarding its contribution to fast and accurate artillery fire, it is necessary to make

some assumptions. For the purpose of this thesis the following simplifying assumptions regarding source of firing errors are made.

a. The other artillery system components (besides the gun section) perform their respective tasks related to timely fire in the time that is expected of them.

b. The aimpoint computed by FDC is the actual location of the target.

   1) No errors are made among the other artillery system components (FO, RADAR, FDC, Survey, Meteorology).

   2) The gun crews do not err when taking measurements for the FDC. Gun crews are periodically asked by the FDC to provide propellant temperatures and muzzle velocities to assist in a better computer solution.

c. The aimpoint of the weapon is the precise impact point of the shell.

   1) Dispersion is disregarded. Artillery fire always experiences normal dispersion in terms of range probable error and deviation probable error about the targeted aimpoint.

   2) No errors are made by the battery leadership during the emplacement of the cannon weapon system. Prior to being set up to fire, the unit leadership emplaces the weapons. Errors occur during this emplacement which, if not corrected, will affect the accuracy of the artillery to follow.

   3) No errors are made when the gun crew performs routine serviceability checks of their weapon. Prior to weapon firing the gun section performs tasks which can later affect accuracy. These tasks deal with such things as sight alignment,

checks to ensure equipment is within tolerance, and emplacement of aiming reference points.

4) No errors occur in sub-systems directly related to the gun section. Events external to the gun crew which may negatively affect the accuracy of the artillery are defective fuzes, defective propellant, a round that fails to seat in the chamber when it is rammed, and an aiming reference point that is inadvertently moved.

2. Assumptions to Facilitate Modeling

a. Battery Homogeneity

Gun sections are organized in batteries which train together and achieve some degree of homogeneity under their common commander. Among the duties of the commander is the establishing of training standards, standard operating procedures, and proficiency standards for the unit. It can be reasonably expected that standards are somewhat uniform across a battery. This uniformity allows for the gathering of unit data rather than individual section data. Within the unit, use of time and human error rates are basically homogenous. Because of battery homogeneity, data generated in one battery is of limited or no use in another battery.

b. Competent Gun Chiefs

A chief is capable. He is competent as a quality assurance inspector of his crew's work. Gun chiefs are required to go through thorough periodic testing to insure

their aptitude at finding all possible crew errors. It is assumed that a chief does not lose his ability to find errors. The chief's competence is such that he perceives his visual tasks as being relatively simple. Inspection failures are the result of random error, not incompetence.

c. Gun Crew Errors are Independent of Each Other

Crew errors are not totally independent. A poorly performing crewman is more likely to set a second error than a superb soldier is of setting his first. The interaction between errors is complex and unpredictable. It would be extremely difficult to model that interaction. The assumption of error independence is a rough approximation of reality to facilitate modeling.

d. Type I versus Type II Error

If the costs of identifying a good product as flawed (Type II error) is minimal compared to the costs of failing to identify a flawed product as flawed (Type I error) then Type II errors can be disregarded with little loss in model validity. This allows for simplification of the model and, in fact, is often the case in quality assurance inspection work. In the artillery gun section Type II error is commonly considered insignificant when compared to Type I error. No chief has ever been ruined by being overcautious

and calling a mission flawed when it was not. Many a chief has been ruined by failing to catch a flawed mission.

e. Simplicity of Visual Inspection Tasks

The visual inspection tasks required on a gun section are relatively simple to a trained cannoneer. The types of errors to be identified do not require a detailed search, exceptional visual acuity, or higher level cognitive skills.

f. Effects of Errors are Cumulative

The errors a gun section makes can often off-set each other such that the full effect of an error is not realized. This model assumes that when multiple errors occur on the same mission that their effects are cumulative along one dimension. Therefore, this is a "worst-case" analysis type model.

IV. MODELING THE ARTILLERY PROBLEM

A. GENERAL CHARACTERISTICS OF THE MODEL

The model to allocate a gun chief's inspection time is a goal program which suggests an amount of time a gun chief should spend on each of thirteen inspection tasks prior to every round fired from his weapon. The suggestion for time use is based on the following criteria for the tasks:

1) The likelihood of crew error;
2) The likelihood of inspector error;
3) The potential costs of the fired error;
4) The commanders' objectives.

The method by which the data are gathered for the model takes into account the characteristics of the artillery weapon system and the level of training of the surveyed unit being analyzed.

B. THE PROBABILITY OF GUN CREW ERROR

Each of the 16 crew tasks which the chief inspects with his 13 visual inspection tasks has a distinct probability for error. Based on the battery homogeneity assumption, a probability for crew error applies across all the gun sections of a battery. As a result of his firsthand knowledge of the phenomenon, the gun chief has a strong

intuitive sense for the relative frequency of errors on the crew tasks that he inspects.

Due to the battery homogeneity assumption and the fact that there are six or eight gun sections to a battery, there are seldom more than eight gun chiefs to give expert judgment on any crew error phenomenon under investigation. The paired comparison technique of estimating error is not viable unless there is a large number of respondents. Thus, the paired comparison technique is not a practical solution for the illustrative problem in this thesis.

The model accepts the gun chief as an expert capable of rendering judgments on relative frequencies of crew errors. The model gathers this individual knowledge by means of a survey. Appendix G contains copies of the surveys administered to the gun chiefs. The survey forces the chief to make enough comparisons to allow for an internal consistency check on his judgments (Saaty [Ref 17]). Those judgments found to be sufficiently consistent are converted to probabilities using the indirect numerical estimation technique (Swain and Miller [Ref 1]) and averaged together (Von Winterfeldt [Ref 29]). The result is a deterministic point estimate of probability for each crew error in the battery. Appendix G shows the structure of the survey. Appendix C demonstrates checking the consistency of

individual surveys. Appendix A gives an example of converting paired comparison survey input into probabilities and the averaging of input from several experts.

C. THE PROBABILITY OF INSPECTOR ERROR

With 13 inspection tasks the gun chief checks the 16 possible crew errors. Four of the crew errors, the four associated with the assistant gunner, are assessed by a single check that a chief makes using a precision tool called a gunner's quadrant. Within certain bounds inspector error is a function of time taken to inspect a crew task. Those bounds for a gun section are explored.

1. A Function of Time

For a fraction of a second at the start of an inspection task the inspector experiences no increase in accuracy performance due to time required for eyes to focus and the starting of the visual search. As the inspector takes more time his probability for successfully identifying an error, given that an error exists, increases at a decreasing rate (Rizzi, Buck, Anderson [Ref 25]). This increase in accuracy performance continues until the inspector spends 1.5 times the standard amount of time he would normally spend on that visual task (Schoonard, Gould, Miller [Ref 24]).

The experimental findings of Schoonard, Gould, and Miller are heavily incorporated to establish an upper bound for the productive use of time for a gun chief performing visual inspection tasks. Schoonard, Gould, and Miller's study [Ref 24] closely approximates the situation in which gun chiefs find themselves when inspecting for crew error. The study picked a technical task, the inspection of integrated silicon circuit chips, requiring trained inspectors. Each inspector had a minimum of six months experience inspecting for faulty chips. The actual visual search required the simultaneous searching for six or more different types of errors followed by a decision to accept or not accept the chip construction. The possible errors ranged from the simple to the complex in terms of the difficulty of discerning them during an inspection. The range of times that inspectors took to inspect a specific chip for errors was 2.7 to 5.4 seconds. In every aspect of the study noted above, Schoonard, Gould, and Miller come extremely close to the situation of a gun chief inspecting for a gun crew error.

The model accepts that from the time the chief starts searching for errors until 1.5 times the standard time spent on that inspection task [Ref 24] the chief experiences an exponentially increasing probability of detecting an error [Ref 25]. At 1.5 times the standard time spent on an

inspection task a competent chief, with no distracting factors, detects 100% of errors (Drury [Ref 26]). If given more than 1.5 times the standard time for inspection the inspector experiences degradation in his performance (Kochhar [Ref 23]).

Drury [Ref 26] and Smith and Barany [Ref 22 and 32] both develop a curve which represents the inspector's probability for accurate inspection results as a function of time. The curve increases at a decreasing rate, forming a gentle, convex curve. The curve is continuous from a minimum time which reflects the time it takes the eye and brain to start a visual search to a maximum time which reflects the limits of human vigilance for simple inspection tasks. The maximum time is assumed to be 1.5 times the standard time spent by the inspector on the task. The function chosen to represent the probability for inspector accuracy curve is:

(4-1) $Y_i = \sqrt{(T_i)}$, $i = 1,...,13$

Where Y_i = probability for inspector accuracy on task i

$T_i = (T_I - T_{MINi}) / (T_{MAXi} - T_{MINi})$

T_I = time chosen to spend on task_i

This curve approximates the curves that Drury [Ref 26, p 264] and Smith and Barany [Ref 32, p 5] found in their work and which are depicted in Chapter II.C.

2. Establishing Standard Time Use on Visual Inspection Tasks

To utilize the experimental findings that greatest inspector accuracy is achieved at 1.5 times the standard amount of time spent on a visual inspection task requires the generation of standard inspection times on all visual tasks. The standard time used to perform each visual inspection task could be gathered by empirical observation, but this illustrative problem uses the alternative of gathering the chief's knowledge of time utilization by means of a survey [Ref 14, p.6-1].

The chief has a strong sense for where his time is spent when he inspects for error. The chief performs paired comparisons of the amount of time spent on various inspection tasks. From the paired comparison data the model derives a point estimate for the time spent per inspection task by the gun chief. By averaging across all chiefs in a battery the model derives a battery estimate for chief's time spent per inspection task. See Appendix C for details on the structuring of a time use survey and of how a time use estimate is derived from actual data.

3. Total Time to Perform All Inspection Tasks

A limit on the total amount of time an inspector is permitted to perform all visual tasks may be determined by a commander. For general purposes of this problem, the Field

Artillery School standard of 30 seconds is the amount of time permitted chiefs to inspect their crews prior to fire [Ref 39, p.3].

D. THE PROBABILITY OF FIRING AN ERROR

For an error to be fired the chief must be inspecting an improperly performed task and fail to identify the error. The probability that the crew performed a given task improperly is a point estimate derived by survey input. The probability that the chief fails to identify the error is a function of time. The model is shown in Figure 8.

A technique in nonlinear programming for evaluating the curve in Figure 8 is shown in Equation 4-2. This technique explicitly models the curve shape shown in Figure 8.

(4-2) $P_{Ii*Ci} = [\ \sqrt{(1 - P_{Ci})^2 \ * \ T_i} \ + \ P_{Ci}\ ]$, i=1,2...,13;

where $T_i = (T_I - T_{MINi}) / (T_{MAXi} - T_{MINi})$, see Equation (4-1);

P_{Ii*Ci} = P(accuracy$_i$) = probability for system accuracy on task$_i$,

P(error$_i$) = 1 - P(accuracy$_i$) = probability for system error on task$_i$.

E. THE COST OF FIRING AN ERROR

The costs for firing an artillery gun crew error range from the insignificant or the unnoticeable to the very significant. Some of the more important costs of a gun crew error being fired are:

1) loss of maneuver force confidence in their supporting artillery;

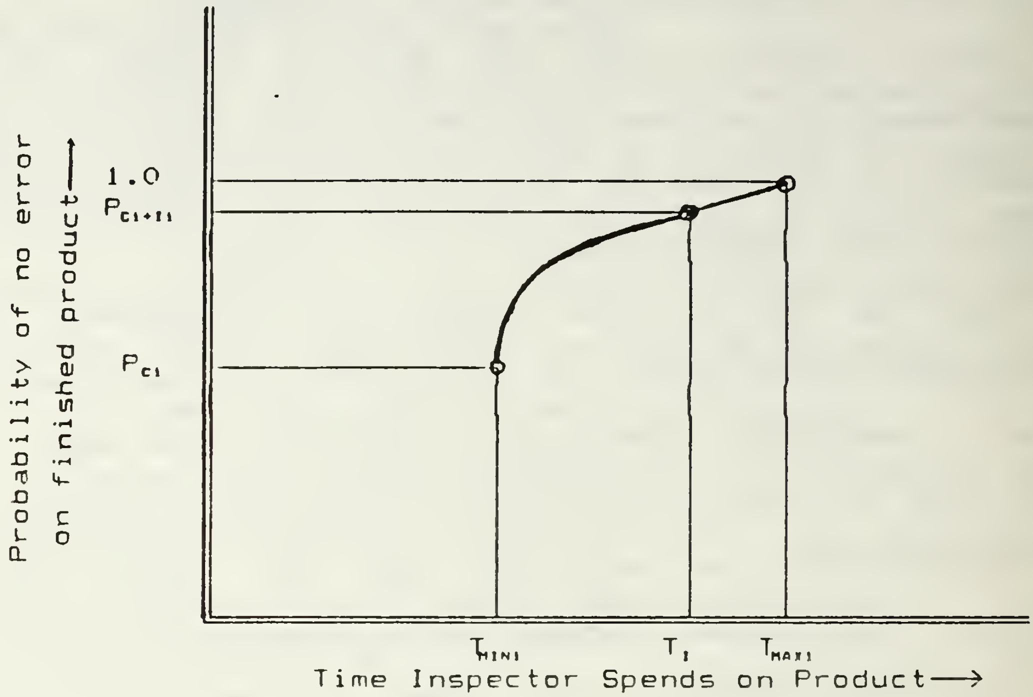
2) the cost of the resupply effort to deliver more ammunition for that which was wasted;

3) loss of destructiveness due to inaccuracy.

The most important costs are directly related to the consequences of interest for the system. Timeliness and accuracy of fire are the consequences of interest to the artillery fire support system.

Each of the 16 crew tasks has a different cost distribution associated with it in terms of inaccuracy (in meters), should the crewman err at performing his task. The model uses the PERT cost estimation technique to determine a cost distribution for each error [Ref 33]. Senior battery personnel that are well versed in both fire direction and gun crew operations determine the largest, the smallest, and the most likely error of each of the 16 error types. Using tabular firing tables [Ref 38] for the battery's weapon system and assuming a range at which targets are most likely engaged, a Beta distribution cost curve (in meters) is established for each error type [Ref 38 and Ref 33]. See Appendix B for details of the PERT cost estimation technique.

The potential number of meters by which a crew error causes the round to miss a target is a good indicator of



P_{CI} = Probablity that worker makes no error on task,
T_{MINI} = Minimum time inspector must spend on task to get any return
T_{MAXI} = Maximum time inspector can spend productively before attention span is exceeded
T_I = Amount of time inspector spends on task
P_{CI+II} = Probablity of no error on finished product
$1-P_{CI+II}$ = Probablity of error on finished product

Figure 8 - Probability of Firing an Error

either the amount of damage that can be expected on the target (small errors) or the amount of maneuver confidence that may be lost (large errors).

F. MULTI-OBJECTIVE CRITERION OF THE COMMANDER

The commander has objectives that he wants accomplished. Suppose, for instance, that a given commander, first and foremost, wants never to lose the confidence of the maneuver force he supports. Second, the commander wants to have effects on target. These hypothetical but realistic objectives of a commander are pursued in the remainder of this model to demonstrate the flexibility and real-world applicability of goal programming.

1. Making a Goal out of First Objective

For the purpose of this problem, assume that the loss of maneuver confidence in their supporting artillery is the most costly and damaging thing that can happen to the fire support system. There is good reason that this may well be true for any artillery unit. Loss of confidence results in hesitance on the part of maneuver to employ artillery and thus increases the chances of losing combat engagements due to lack of firepower.

Confidence is difficult to quantify and place on some continuous scale. Therefore, a crew error cannot be directly linked to an amount of confidence lost by the maneuver force

towards its supporting artillery. It is intuitive that a miss by a large number of meters corresponds to a larger loss of confidence by the maneuver whereas a small miss may be mistaken as normal dispersion and thus goes unnoticed. Therefore potential number of meters by which a crew error causes the round to miss a target suffices as a surrogate for the amount of confidence lost.

Below a certain distance threshold, maneuver confidence is not lost by artillery which misses its target. Artillery is an area fire weapon and it is expected by those who employ it that artillery will hit in the general vicinity for which it was called. Within that vicinity, or expected area of impact, the cost of crew error is just the cost of missing the target and the cost of wasted ammunition.

The maneuver confidence radius represents the maximum distance from the target that a round can hit and still maintain the confidence of the maneuver force being supported. The commander's first goal is that his rounds must hit within the maneuver confidence radius of the targeted aimpoint. The commander needs to specify a maneuver confidence radius.

2. Making a Goal out of the Second Objective

The commander's second objective, getting effects on target, is clearly a function of both the accuracy of the fire and the timeliness of the fire. If accuracy is sought at the

excessive expense of time then the target will likely move and escape destruction. If timeliness is sought at the excessive expense of accuracy then the target will escape destruction due to rounds missing the aimpoint. A trade-off between time and accuracy is required to get effects on the target. The commander needs to specify the accuracy and timeliness goals.

G. GOAL PROGRAM FORMULATION

In the proposed multi-objective problem there are two objectives: avoid any loss of maneuver confidence and get effects on target. One goal is on the first tier: hit within the maneuver confidence radius of the target. Associated with the second objective is a tier of goals. On the second tier is an accuracy goal and a timeliness goal that the commander specifies based on his weapon system and the targets on which his weapon systems will most likely be employed.

This two-tiered set of goals lends itself to multi-objective, preemptive goal programming. On the first tier is the commander's goal of keeping maneuver confidence. Once inspector time is allotted and this first goal is achieved then the second tier of goals is considered.

1. Decision Variables

In goal programming to achieve allocation of visual inspection resources, inspector time spent on checking the work of others is the decision variable (X_i, i=the number of

visual inspection tasks). The purpose of this goal programming is to achieve a most satisfactory allocation of inspector time.

2. System Constraints

The minimum and the maximum amounts of time that can be spent productively on each of the tasks are the two system constraints. These limits are based on the experimental findings of Drury [Ref 26] and Schoonard, Gould, and Miller [Ref 24]. Drury found a minimum amount of time required for an inspector's eyes, brain, and nervous system to function and start a visual search for error. Schoonard, Gould, and Miller found a maximum amount of time that an inspector spends at a visual inspection task before performance declines due to the limits of human vigilance.

3. Goal Constraints

There is not a single deterministic cost associated with each system error. There are three costs: a maximum, a minimum, and a most likely cost. Using the PERT cost estimation technique a Beta distribution curve is generated to fit these costs. Visual inspection tasks are related to accuracy goals through their individual beta cost functions.

Visual inspection tasks fall into consideration in tier one if their minimum possible cost exceeds the maneuver confidence radius. Visual tasks fall into consideration in

tier two if their maximum possible cost exceeds the maneuver confidence radius. Tier three visual tasks have maximum possible costs below the maneuver confidence radius.

Time is allotted by tier, thus reflecting the commander's priorities. The total amount of time required to fully satisfy (1.5 times the standard time) all visual tasks residing in a tier is compared to the total inspector time available. If time required is less than time available then all visual tasks in the tier are allotted a full complement of time and the model moves to the next tier of tasks. If time required to fully satisfy all visual tasks in a tier is greater than the time available then the goal program is run to determine allocation of inspection time among the visual tasks residing in the tier.

Tasks within tiers are handled with the same goal constraints. These goal constraints are elastic, allowing some deviation if insufficient resources are available to satisfy all goals.

The goal constraints are:

(4-3)

$$\text{tier 1} \quad \sum_{n=1}^{N} X_n - TPOS + TNEG = TIMEGOAL_1$$

for all tasks n where minimum cost $task_n \geq MCR$,

$$\text{tier 2} \quad \sum_{p=1}^{P} X_p - TPOS + TNEG = TIMEGOAL_2$$

for all remaining tasks (13 - N) where maximum cost of $task_p \geq MCR$,

$$\text{tier 3} \quad \sum_{q=1}^{Q} X_q - TPOS + TNEG = TIMEGOAL_3$$

for all remaining tasks where (N + P + Q) = 13.

$TIMEGOAL_1$ is the overall goal for time in which all tasks are to be completed. $TIMEGOAL_2$ is the amount of time remaining from $TIMEGOAL_1$ after the first tier tasks are satisfied. $TIMEGOAL_3$ is the amount of time remaining from $TIMEGOAL_1$ after the first and second tier tasks are satisfied.

(4-4)

$$\text{tier 1} \quad \sum_{n=1}^{N}[P(error_n) * MAXCOST_n] - ACCPOS + ACCNEG = 0$$

for all tasks n where minimum cost $task_n \geq MCR$,

$$\text{tier 2} \quad \sum_{p=1}^{P}[P(error_p) * MAXCOST_p] - ACCPOS + ACCNEG = 0$$

for all remaining tasks (13 - N) where maximum cost of $task_n \geq MCR$,

$$\text{tier 3} \quad \sum_{q=1}^{Q}[P(error_q) * MEANCOST_q] - ACCPOS + ACCNEG = 0$$

for all remaining tasks where (N + P + Q) = 13,

where $P(error_i)$ = the probability of system error on $task_i$ from Equation 4-2,

$MAXCOST_i$ = maximum cost of $task_i$ (see Appendix B),

$MEANCOST_i$ = mean cost of $task_i$ (see Appendix B).

MCR = maneuver confidence values

The right hand side of the constraint represents a goal in terms of accuracy (in meters) that the commander wants to be met.

4. Achievement Function

The commander assigns a weight to the time goal deviation and the accuracy goal deviation in the model. The commander must weight the deviations from each goal with respect to their relative importance to the fire support system. The purpose of the goal program is to simultaneously minimize deviations from goals within tiers.

The commander is generally aware of the type of combat in which he will be employed and the type of targets on which he will be called to deliver his fires. Most targets of opportunity have the potential to move at some rate. That rate (meters per second) provides the commander the knowledge he needs to make a trade-off between timeliness of fire and accuracy of fire. The commander expresses this trade-off by the weight he assigns to the respective goal deviations.

The appropriate weight is multiplied times the deviation variable for each goal. The two weighted values are then summed to equal a total deviation for the problem. The achievement function minimizes this total deviation value. As the goal program iterates, it trades off accuracy for time

or time for accuracy until a solution is reached which best satisfies the two goals in light of their respective weights.

The achievement function is given in Equation 4-5.

(4-5)

Minimize:

DEVIATION = (TIMEWT * TPOS) + (ACCWT * ACCPOS).

V. APPLICATION TO ACTIVE ARMY UNIT

A. CURRENT ALLOCATION OF INSPECTOR TIME

The competent chief will attempt to at least look at every one of the 16 error-prone tasks accomplished by his crew. The chief's underlying belief is that he is a good inspector and that if he looks at the possible error he will likely catch the error if it is present.

The following are the keys to modeling the current allocation of chief's time on the pre-fire inspection:

1) The gun chief spends at least the theoretically derived minimum time for a visual inspection task on every task.

2) The gun chief spends additional time on those tasks that he knows are more frequently in error than others in the attempt to catch as many errors as he can.

3) The chief does not trade time for accuracy. He shoots within the time required of him (30 seconds) and checks as best he can (using rule 1 and 2) during that period of time.

The model proposed is simple, yet it mirrors the chief's decision making process quite well. The idea behind the current use of inspector time is summed up by the one goal: stop all errors within the time constraint to shoot. A GAMS program which reflects these priorities and uses the probabilities for error developed in this thesis is shown in

Appendix E. The allotment of inspector time resulting from this model is shown in TABLE 2.

B. ALTERNATIVE ALLOCATION OF INSPECTOR TIME

The following are the keys to modeling the alternative allocation of chief's time on the pre-fire inspection:

1) Visual inspection tasks covering crew errors with minimum possible costs that exceed the maneuver confidence radius must be considered first for allocation of inspection time. The maximum possible costs of the errors are considered when the allocation of time is made.

2) Visual inspection tasks covering crew errors with maximum possible costs that exceed the maneuver confidence radius are considered next for allocation of inspection time. The maximum costs of the second tier errors are considered when the allocation is made.

3) Visual inspection tasks covering the remaining errors are considered last for allocation of inspection time. The expected costs of the third tier errors are considered when the allocation is made.

The alternative model incorporates this information before allocating inspector time. In this example of an alternative plan for the use of the inspector's time the commander's goal is to stop costly errors. The value that drives the goal, in this instance, is maneuver force confidence and target destruction. The results will be different than the current allocation of inspector time which was driven by the inspector's goal of stopping all errors.

Appendix E gives the GAMS computer runs of both the current and alternative allocation of inspection time by an active army unit surveyed at Fort Ord, California. TABLE 2 shows the different allotments of inspector time per inspection task that resulted from the two model runs.

TABLE 2. CURRENT VS ALTERNATIVE ALLOTMENT OF INSPECTOR TIME

Inspector Task	Current Allotment	Alternative Allotment	Difference Col2 - Col1
G1	2.24	2.80	+ .56
G2	2.56	1.05	- 1.51
G3	1.00	1.00	0
G4	1.60	1.46	- .14
AG	7.21	8.90	+ 1.69
A1	1.80	1.80	0
A2	1.78	.75	- 1.03
A3	1.70	1.27	- .43
A4	3.40	3.40	0
S1	1.14	3.00	+ 1.86
S2	2.00	2.00	0
S3	2.15	3.50	+ 1.35
S4	1.40	1.23	- .17

VI. CONCLUSIONS AND RECOMMENDATIONS

A. CONCLUSIONS

Visual inspection to identify worker error often involves trained inspectors to perform a task requiring technical expertise. Human accuracy at visual inspection tasks is generally a function of the time taken to inspect. Inspector accuracy at positively identifying existing errors increases at a decreasing rate as a function of time. There are lower and upper bounds on the time axis creating a range of time over which this increasing inspector accuracy is a continuous variable. Those bounds have been explored experimentally and are available for use by systems analysts.

If the possible human errors on a work site can be identified then expert judgments of the personnel involved in the actual operational work can be used to derive the probability for worker error on each task. In the same way, the standard time an inspector spends on the inspection of the task can be derived. Costs of system failures resulting from task error can be estimated by the management.

The expected cost of doing business can be written as a function of inspector time spent on each component task in the system. If the decision maker can establish goals for the

system cost of a product and the acceptable amount of time for an inspector to spend on the product, then goal programming provides a method for the organization to optimize the use of inspector time.

B. POSSIBLE APPLICATIONS OF METHODOLOGY

Small-scale operations that employ visual inspectors to check the work of production personnel are prime candidates for use of this methodology. The small-scale operation is emphasized because it is most likely one in which a formal system analysis has not been conducted to evaluate optimum times for visual inspection or optimal rates by which production must occur.

An abbreviated but effective systems analysis approach to the proper utilization of inspector time requires only a few probability estimations and a few cost estimations. The fact that the personnel on the weapon systems can provide the probability of error information and the unit leaders can provide the cost of error information means that individual units can apply systems analysis to better achieve their goals.

The pace at which the product is presented to the visual inspector has everything to do with whether the visual inspection will have the desired effect of the management or not. In this case a little bit of math goes a long way. By

using eigenvalues to establish validity of expert judgments, the model considers only those respondents whose judgments are consistent. Some adding, multiplying, and dividing achieves probabilities for each crew error. The cost estimation technique uses a simple beta distribution to model the cost distribution for each error. The model requires only three rough estimates on the part of a knowledgeable manager. The mean of the cost distribution is achieved by some subtraction and division. The probability of inspector error and the final cost of doing business is determined by goal programming. The input for the goal constraints are obtained from the decision maker. The result is a recommendation, by task, for the use of inspector time such that the organization goals are met as closely as possible.

C. AREAS FOR FUTURE RESEARCH

A curve fit on some experimental results done in the 1970's on the relationship between time spent on a visual inspection task and the accuracy of the inspector at positively identifying existing errors yielded a curve of

$$P(IA) = \sqrt{T} ,$$

where P(IA) is the probability of inspector accuracy and T is the time the inspector takes to inspect.

This is basically the curve used for all visual inspection tasks in the illustrative problem used in this thesis. An

area for future research is classifying different curves with different levels of difficulty of the visual inspection. It appears from the experimental results that with an increase in difficulty in the visual task, the rate of improvement in accuracy changes from increasing at a decreasing rate to increasing at a slower, more constant rate. If error-prone visual inspection tasks can be rated according to difficulty and different accuracy curves can be generated for difficulty levels then the model may be more valid.

Another area that may yield interesting results is weighing of the various expert judgments using some criteria. Suggested criteria that are readily discernable from the respondents are time in service, time in the job, rank, and skill qualification test score. Weighted judgments may yield probabilities that are more reliable or verifiable than giving each respondent equal weight in their input to unit error probabilities. It may be determined that certain qualifications are significantly more important than others in the development of a gun chief.

The model developed is entirely deterministic. The model develops probability and time estimates from several sources. From the several estimates a distribution could be established with a standard deviation on the mean point estimate. The cost estimate procedure using PERT methods generates a Beta

distribution for costs of each error. A simulation could be developed incorporating the distributions from all the data collected in this model which would yield a more robust solution. By running the simulation a number of times, confidence intervals for the various errors could be generated.

This thesis put time and probability phenomena on an interval scale of measurement by using paired comparisons and indirect numerical estimation methods. The anchoring of that interval scale to a ratio scale was done by direct numerical estimation of some single phenomenon by the respondents. Direct numerical estimation has flaws as a technique for gathering data from operational personnel. An area for future research would be to design an experiment and generate actual values from empirical observation for the estimates which anchor the interval scaled values to a ratio scale.

APPENDIX A

GENERATING PROBABILITIES FOR CREW ERROR

The steps to generate probabilities for crew error using expert judgment are given below with a numeric example taken from survey input out of an active army unit.

1. Create a fault tree. See Figure 9. Worker errors appear in the lowest, or first level. Errors are grouped by worker, by work station, or by some other criteria that is easily discernable by the inspector. Those criteria form a second level of the fault tree and fall under the general category of "error". "Error" and "no error" form the third level of the tree.

2. Gather survey responses from inspectors. Inspectors are called on to relay their firsthand knowledge of relative frequencies of errors. Inspectors do pairwise comparisons as to relative frequencies of errors within criteria groups. When all groups have been judged then pairwise comparisons as to relative frequencies are performed on the groups themselves. Finally a direct numerical estimation is made by the inspector as to the frequency of missions that occur which have any error. A sample survey used in an artillery unit is included in Appendix G.

3. Turn survey responses into a reciprocal matrix. Ones appear on the main diagonal. Survey responses of relative frequencies fill the upper triangular matrix and their reciprocals fill the corresponding positions in the lower triangular matrix. See Table 2.

4. Derive the maximum eigenvalue and the eigenvector for the reciprocal matrix. The eigenvector is the relative frequency of each error from the perspective of one respondent. See Table 3. The maximum eigenvalue is used in Appendix C to derive a measure of consistency for the respondent.

5. Turn frequency scores into probabilities. By normalizing the eigenvector (making its components sum to one) the probability for each error is derived, given that some error within that group of errors did occur. See Table 4.

6. Across all consistent responses within a unit (use method in Appendix C to establish consistency), average the probability of each error type to make a unit probability. See Table 5. Fill those unit average probabilities back on the fault tree in the P(j), P(k), P(l), P(m), and P(n) positions. See Figure 10.

7. Take the direct numerical estimates of the probability for a fire mission containing an error of any sort. Average

them for a unit probability of fire mission error. Fill this value in on the fault tree in the $P(i_1)$ position.

8. Use the multiplicative rule down each branch of the fault tree to derive a probability for each type of error on the first level.

TABLE 3. RECIPROCAL MATRIX FOR GUNNER ERROR FREQUENCY.

(taken from a respondent's survey on gunner errors)

relative frequency of errors		error type 1	2	3	4
error type	1	1.00	1.00	3.00	3.00
	2	1.00	1.00	2.00	2.00
	3	0.33	0.50	1.00	1.00
	4	0.33	0.50	1.00	1.00

TABLE 4. EIGENVECTOR FOR THE RECIPROCAL MATRIX

error type 1	.718
error type 2	.587
error type 3	.263
error type 4	.263

TABLE 5. NORMALIZED EIGENVECTOR

Eigenvector normalized to make probabilities:

error type 1	.39
error type 2	.33
error type 3	.14
error type 4	.14

TABLE 6. AVERAGE OF RESPONDENT'S ESTIMATES

Average of five consistent respondents' probabilities.

error type 1	.30
error type 2	.36
error type 3	.18
error type 4	.16

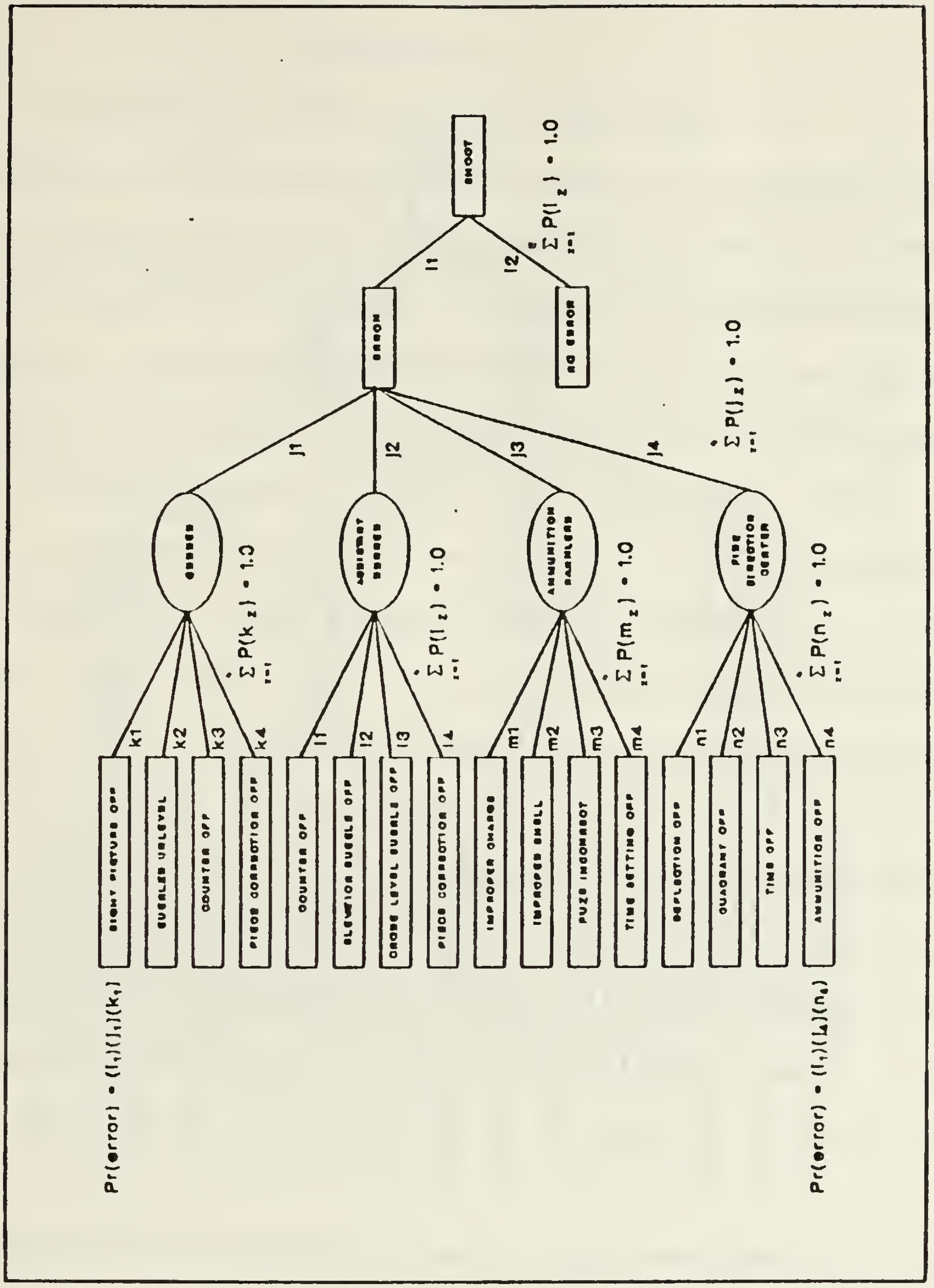


Figure 9 - Probability of Crew Error Fault Tree

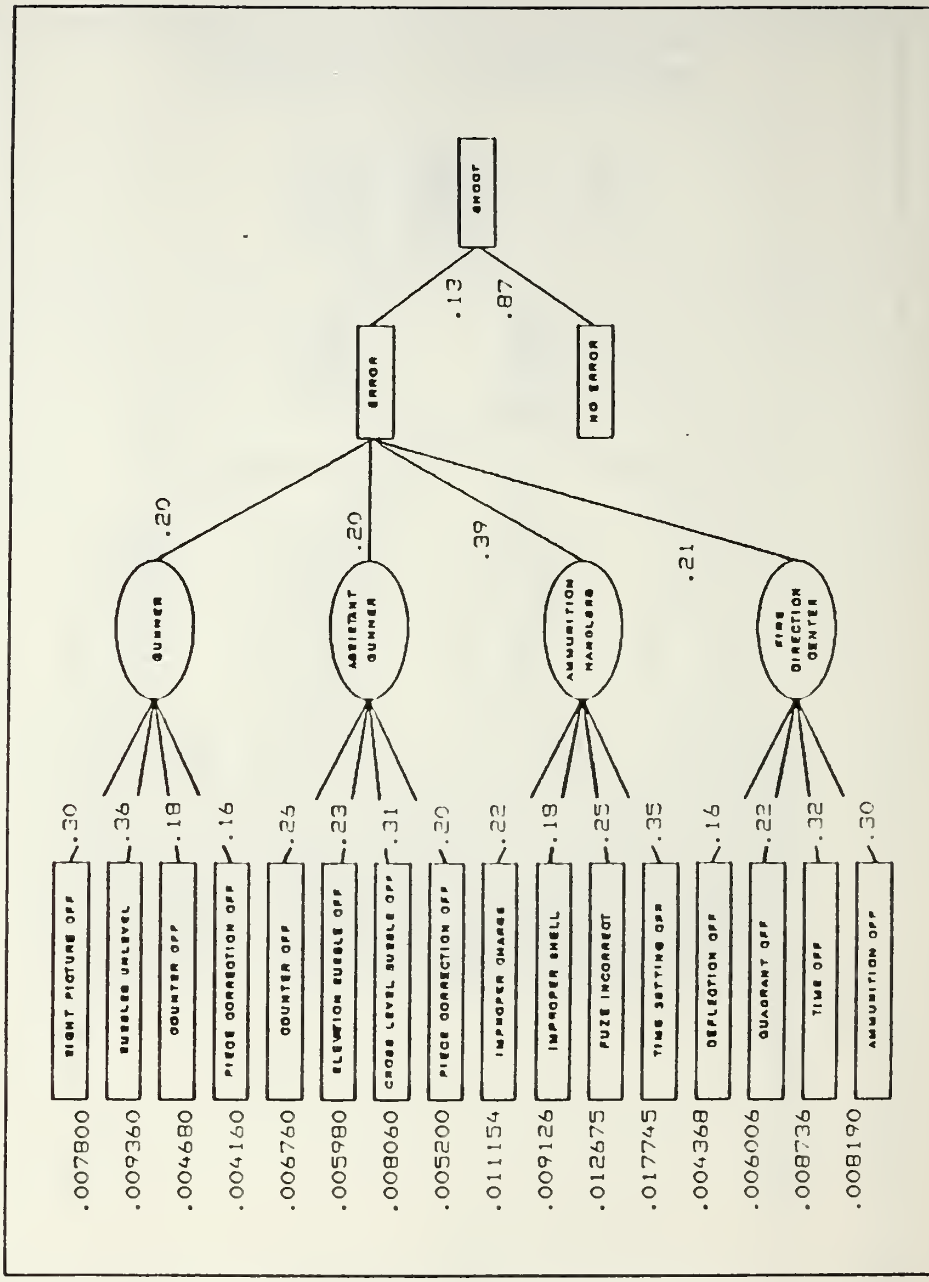


Figure 10 - Probability of Crew Error Data

APPENDIX B.

GENERATING COST ESTIMATES FOR ERROR

Crews make errors and inspectors fail to identify those errors. The costs that result are measured in meters by which the error is expected to cause the round to miss the target. Each error has a maximum amount that it can cost the system. That maximum is affected by such things as unit standard operating procedures and unit safety measures which may preclude an extreme error. One example is the M102 howitzer. When traversed, the entire metal structure pivots on a ball mounted to a base plate. If traverse limits exist for firing safely then it is a common technique to drive metal stakes in the ground abutting the metal structure when it is lined up to fire on the left and right traverse limits thus physically limiting the weapon to firing within safe traverse limits. The result is an administrative method of precluding gross firing errors to the left or right of the target area. This naturally reduces the possible cost of traverse, or deflection error.

Because there are many procedures in the field on five different cannon weapon systems for precluding various firing errors, there exist no minimum and maximum costs for crew

errors that apply across the army. It is within the means of senior personnel in each unit, however, to consider the unit's procedures and weapon system to establish a minimum, maximum, and modal value for each error type. The steps to take in establishing the key values for each error type are reviewed.

1. Assume an average range at which targets are engaged. Assume a charge with which those targets are engaged.

2. Extract information from the tabular firing tables (TFTs) for the respective range and charge assumed. Information to be extracted is the effect (measured in meters) of a round that, when fired, is off by:

   a) 1 mil in elevation

   b) 1 mil in deflection

   c) 1 square weight

   d) 1 charge of propellant

   e) 0.1 second on time fuze setting

3. Consider unit procedures that effectively limit the size of errors that can possibly be fired. Determine a maximum amount of error that can be set by a worker in terms of the items listed above (mils, square weights, charges, seconds) and convert that amount to meters on the ground.

4. Given that he must set an error, determine a minimum amount of error that a crewman can possibly set. For example, a crewman can set no less than a one charge error without performing perfectly in that regard. So the minimum possible error for charge is that number of meters corresponding to a one charge error.

5. Given that he must set an error, determine a most likely error that can be fired.

In the case of a 105 mm artillery unit at Fort Ord, California, the following assumptions were made about the potential costs of the various inspection task errors.

1) Safety Ts used,

2) Safety stakes employed,

3) Dog-legged safety box in impact area,

4) Charge 5 propellant required,

5) Range of target: 6,000 meters.

The following matrix was developed from the expertise of several unit leaders.

TABLE 7. COST OF FIRING A CREW ERROR (IN METERS)

Inspection Task	estimated from experience: Min Cost	Modal Cost	Max Cost	computed assuming a Beta Distribution: Mean Cost	Std Devn
G1	0	30	2400	420	400
G2	0	10	200	40	33
G3	0	60	2400	440	400
G4	0	15	400	74	66
AG	0	20	2600	447	433
A1	950	1200	2400	1358	242
A2	25	30	100	41	12
A3	0	20	120	33	20
A4	0	100	2500	483	417
S1	10	120	2400	481	398
S2	15	130	2000	422	330
S3	25	260	2500	594	412
S4	0	100	150	92	25

APPENDIX C.

GENERATING TIMES FOR INSPECTION TASKS

Two methods are suggested by the NRC for generating standard times for inspection tasks to be completed. One is by measuring empirical observations and the other is by expert judgment. Making empirical observations is the preferred method and is the one suggested if a unit has the time and resources to devote to an experiment to measure a number of observations.

The steps to generate standard times for inspectors to inspect for crew error (using expert judgment) are given below with a numeric example taken from survey input out of an active army unit.

1. Create a fault tree of crew tasks. See Figure 10. Worker errors should appear in the lowest, or first level. Errors are grouped by worker, by work station, or some other criteria that is easily discernable by the inspector. Those criteria form the second level of the fault tree.

2. Gather survey responses from inspectors. Inspectors are called on to relay their firsthand knowledge of relative lengths of time required to inspect for various errors. Inspectors do pairwise comparisons as to relative lengths of

time to inspect for errors within criteria groups. When all groups have been judged then pairwise comparisons as to relative lengths of time required to inspect the groups of errors themselves are done. Finally a direct numerical estimation or an empirical measurement is made by management of the time required to inspect for one task.

3. Using the one task as a reference point, all other tasks are given a length of time for inspection. When an estimate exists for all tasks then a unit average is taken and that becomes the standard inspection time for the unit.

APPENDIX D

CONSISTENCY CHECKS ON SUBJECTIVE EVALUATIONS

The method for checking internal consistency of a set of pairwise comparisons made by a respondent is reviewed. This particularly applies to comparisons of relative frequency of various events, such as event A is three times more likely that event C.

1. Follow steps 1 through 4 of Appendix A to derive a maximum eigenvalue for the respondent's reciprocal matrix.

2. Generate a consistency index (CI) for the respondent's matrix by

$$[\ \lambda_{max} - N\ ]\ /\ [\ N-1\ ] = CI.$$

3. Generate a quantity of random reciprocal matrices of the same dimension and containing the same range of values as was possible to the respondents on the survey they were administered. The main diagonal of these matrices are ones. The upper triangular cells of the matrices are filled with values picked at random from the possible range. Complete the lower triangular cells with the corresponding reciprocal values of the upper triangular cells. Compute the maximum eigenvalue for each matrix and average all of the maximum eigenvalues together. The result is an estimated maximum

eigenvalue for a respondent who gives totally random responses to the original survey.

4. Generate a consistency index for the random matrix [CI_{random}]:

$$[\ \lambda_{MAXrandom} - N\ ]\ /\ [\ N - 1\ ]\ =\ CI_{random}.$$

5. Generate a consistency ratio by

$$(\ CI_{respondent}\ )\ /\ (CI_{random}) = CR.$$

If CR is less than or equal to .10 then there is a sufficient level of internal consistency in the respondent's judgments to consider them for analysis work [Ref 17, p.83].

Step number three above requires some effort and significant computer resources on the part of an analyst. This step is made considerably easier if the analyst prepares the respondent's survey so that only values between one and nine (and their reciprocals) can be selected by the respondent. The range of one to nine recurs frequently in human judgments. For this range of values Saaty [Ref 17] generated consistency indices (CI) for random reciprocal matrices from size (3 X 3) to (10 X 10). Table 7 shows the random consistency indices for matrices up to (10 X 10).

TABLE 8. Random Consistency Indices (CI_{random})

N X N	2	3	4	5	6	7	8	9	10
CI_{random}	0.00	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.49

APPENDIX E

USING GAMS FOR GOAL PROGRAMMING

GAMS is used to perform the allocation of inspection time by the Current Model and the Alternative Model.

1. The Current Model

In the Current Model the chief is aware of only the inspection tasks he must perform, the relative frequency by which the tasks are successful at discovering crew error, and the relative amount of time it takes to perform the visual tasks. Given only that much information the chief's strategy is to stop as many crew mistakes as he can in the time allowed. The assumption is made that the chief's intuition works very well with the knowledge that he has and that he does accomplish his objective of minimizing the probability for a crew mistake. It is reemphasized that the chief does not consider the relative magnitude of the costs of the mistakes when he currently performs the pre-fire inspection. The GAMS program for currently allocating inspection time is labeled "Current Model".

2. The Alternative Model

The Alternative Model takes what the chief knows in the Current Model and then takes into account the costs of the errors. The purpose of the Alternative Model is to not make

costly mistakes while meeting the commander's guidance for fast and accurate fires. In the first tier of the preemptive goal program any inspector error which has a minimum cost greater than the commander's maneuver confidence radius (600 meters for the illustrative problem) is considered. Any first tier error will certainly have a huge negative effect on the artillery system. Every possibility for first tier error must be precluded. This is done by placing a large weight (BPWT) on any positive deviation from the accuracy goal.

In the second tier of the preemptive goal program any inspector error which has a maximum cost greater than the commander's maneuver confidence radius is considered. Any second tier error potentially has a huge negative effect on the artillery system. After first tier errors are precluded then every possibility for a second tier error is precluded. Again, this is done by placing a large weight (BPWT) on any positive deviation from the accuracy goal.

In the third tier of the preemptive goal program all remaining inspector errors are considered. Time that remains after the first and second tier errors are precluded is now allotted to the third tier inspection tasks. The commander now weights timeliness of fire and accuracy of fire relative to each other. In the illustrative problem the commander chooses to weight them equally (TIMEWT = BPWT = 1.0).

An asterisk in the first column of the GAMS computer input is a line that the computer program does not read. In the Alternative Model (2) asterisks are used in the PARAMETERS part of the program so that only the inspector tasks for the particular tier being considered are entered into the program. The GAMS input for the Alternative Model's first tier (2) is given. The second tier and third tier are the same programs but different tasks are allowed or disallowed by using asterisks. In each of the three tiers the SCALARS change to reflect the tier. The first tier starts with 30 seconds of time available (RESPTIME). The weights for time deviation (TIMEWT) and accuracy deviation (BPWT) are 1:600. The second tier starts with 28.2 seconds of time available. The weights for time and accuracy deviation remain 1:600. The third tier starts with 3.6 seconds of time available. The weights for time and accuracy deviation become 1:1.

3. The Output

a) The Current Model output is shown first. The allocation of time by the Current Model for each inspection task is shown in the column labeled LEVEL between the LOWER and UPPER limits. This appears near the bottom of the page of GAMS computer output.

b) The Alternative Model output is on three pages. At the bottom of the first page is the allocation of time for those tasks identified as in the first tier (task A1).

c) At the bottom of the second page is the allocation of time for those tasks identified as in the second tier (tasks G1, G3, AG, A4, S1, S2, S3).

d) At the bottom of the third page is the allocation of time for those tasks identified as in the third tier (tasks G2, G4, A2, A3, S4).

1. The Current Model.

GPNLP2

```
                                CURRENT MODEL
*****************************************************************
  SET
    I  thirteen inspection tasks in four categories
       /G1,G2,G3,G4,AG,A1,A2,A3,A4,S1,S2,S3,S4/;
*****************************************************************

  PARAMETERS

******************************************************************
* these min times are theoretical; based on experiments of min time for
*  eyes to focus and mind to grasp what eyes are seeing

   MIN(I) min time possible on task i- theoretical  seconds

       /G1      .7
        G2      .7
        G3      .7
        G4      .7
        AG     2.0
        A1      .7
        A2      .7
        A3      .7
        A4      .7
        S1      .7
        S2      .7
        S3      .7
        S4      .7 /

*****************************************************************
* these times incorporate theoretical 1.5 times max values of standard
*   time taken by gun chiefs to perform the task.  This is time needed
*   to insure (100%) that task is done correctly.

   MAX(I) max time spend on task i - from paired comparisons


       /G1     2.8
        G2     3.2
        G3     1.0
        G4     1.6
        AG     8.9
        A1     1.8
        A2     4.8
        A3     1.7
        A4     3.4
        S1     3.0
        S2     2.0
        S3     3.5
        S4     1.4/
*****************************************************************
  NEPROB(I) probability of no crew error task i - detm by INE method

       /G1     .992200
        G2     .990640
        G3   - .995320
        G4     .995840
```

The Current Model (continued).

GPNLP2

```
            AG     .974000
            A1     .988846
            A2     .990874
            A3     .987325
            A4     .982255
            S1     .995632
            S2     .993994
            S3     .991264
            S4     .991810/

**********************************************************************
  EPROB(I) probability of crew error on task i -  detm by INE method

           /G1     .007800
            G2     .009360
            G3     .004680
            G4     .004160
            AG     .026000
            A1     .011154
            A2     .009126
            A3     .012675
            A4     .017745
            S1     .004368
            S2     .006006
            S3     .008736
            S4     .008190/

**********************************************************************
* A chief does not consider the costs of various errors as he determines
* where he will spend his time during the inspection.  His sole objective
* is to stop as many errors as possible in the time alotted
*********************************************************************


**********************************************************************
  SCALARS
     RESPTIME  total time allowed for guns to shoot     / 30.0/

**********************************************************************
  VARIABLES
     X(I)       time to be spent inspecting each task in battery
     DEVIATION  deviation from the objective function;

**********************************************************************
  POSITIVE VARIABLES
     X(I);

**********************************************************************
  EQUATIONS
     OBJDEF achievement function
     TLIMIT time limit;
*******************************************************************
* this equation sums the probability for system error (which is a
* function of the decision variable) across all the visual inspection
* tasks AND assigns that sum a variable name of DEVIATION.

```

The Current Model (continued).

GPNLP2

```
* MINIMIZE
     OBJDEF..  DEVIATION =E=
               (  SUM ( I,
     ( 1 - SQRT( (SQR(EPROB(I))) * (X(I)-MIN(I)) / (MAX(I)-MIN(I)) )
         - NEPROB(I) )                    )    );

*****************************************************************
* this constraint limits time spent by the inspector across all visual
* inspection tasks to less than or equal to the commander's goal.

* SUBJECT TO
     TLIMIT..  SUM ( I, X(I) )  =L=  RESPTIME  ;

*  ADDITIONAL CONSTRAINTS involving min and max times allowed.  These
*  keep x in the feasible region as problem iterates, otherwise stops

             X.LO(I) = MIN(I)*1.01;
             X.UP(I) = MAX(I);

*  If region is convex, then no matter where program starts, the
*  solution will be the same.  This forces program to start internally
*  on the convex region because funny things happen on the edges

             X.L(I)  = MIN(I)*1.02
                                                       ;
  MODEL GPNLP2 /ALL/;
  SOLVE GPNLP2 USING NLP MINIMIZING DEVIATION;
```

2. The Alternative Model.

GPNLP2

```
                        ALTERNATIVE MODEL (first tier)
**************************************************************************
* THIS MODEL PERFORMS FIRST TIER OF PREEMPTIVE GP (ON THOSE TASKS WITH
* MIN COST GREATER THAN THE MANEUVER CONFIDENCE RADIUS = 600m)

*resp time  ballpark  ti.wt.  bp.wt
*  30     /    0     /   1   /  600 /
*

***************************************************************************
  SET
    I   thirteen inspection tasks in four categories
        /
*         G1,
*         G2,
*         G3,
*         G4,
*         AG,
          A1
*           ,
*         A2,
*         A3,
*         A4,
*         S1,
*         S2,
*         S3
*           ,
*         S4
            /;
***************************************************************************

  PARAMETERS

***************************************************************************
* these min times are theoretical; based on experiments of min time for
*  eyes to focus and mind to grasp what eyes are seeing

   MIN(I) min time possible on task i- theoretical  seconds

        /
*         G1      .7
*         G2      .7
*         G3      .7
*         G4      .7
*         AG     2.0
          A1      .7
*         A2      .7
*         A3      .7
*         A4      .7
*         S1      .7
*         S2      .7
*         S3      .7
*         S4      .7
                     /

***************************************************************************
* these times incorporate theoretical 1.5 times max values of "normal"
*   time taken by gun chiefs to perform the task.  This is time needed
```

The Alternative Model (continued).

GPNLP2

```
*   to insure (100%) that task is done correctly.

   MAX(I) max time spend on task i - from paired comparisons


         /
*        G1     2.8
*        G2     3.2
*        G3     1.0
*        G4     1.6
*        AG     8.9
         A1     1.8
*        A2     4.8
*        A3     1.7
*        A4     3.4
*        S1     3.0
*        S2     2.0
*        S3     3.5
*        S4     1.4
                 /
*******************************************************************************
  NEPROB(I) probability of no crew error task i - detm by INE

         /
*        G1     .992200
*        G2     .990640
*        G3     .995320
*        G4     .995840
*        AG     .974000
         A1     .988846
*        A2     .990874
*        A3     .987325
*        A4     .982255
*        S1     .995632
*        S2     .993994
*        S3     .991264
*        S4     .991810
                      /

*******************************************************************************
  EPROB(I) probability of crew error on task i -  detm by INE

         /
*        G1     .007800
*        G2     .009360
*        G3     .004680
*        G4     .004160
*        AG     .026000
         A1     .011154
*        A2     .009126
*        A3     .012675
*        A4     .017745
*        S1     .004368
*        S2     .006006
*        S3     .008736
*        S4     .008190
```

The Alternative Model (continued).

GPNLP2

```


***********************************************************************
* these costs are derived using 2 criteria.  First - mean cost is based
*  on data from firing tables assuming range to target 6000 meters, and
*  beta distribution (pert estimation techniques).  Second - max cost
*  is based on data derived from firing tables.

  MCOST(I) mean cost of error i -  detm by PERT  Beta distn techn


* SET 2 (max costs)
       /
*        G1   2400
*        G2    200
*        G3   2400
*        G4    400
*        AG   2600.
         A1   2400.
*        A2    100.
*        A3    120.
*        A4   2500.
*        S1   2400.
*        S2   2000.
*        S3   2500.
*        S4    150.
                  /

***********************************************************************
  SCALARS
     RESPTIME  total time allowed for guns to shoot    / 30.0/
     BPARK     number meters in which aimpoint must be /  000/
     TIMEWT    weight placed on time pos devn in OBJ   /  1.0/
     BPWT      weight placed on error pos devn in OBJ  / 600 /;

***********************************************************************
  VARIABLES
     X(I)        time to be spent inspecting each task in battery
     TOFF        deviation from the time goal constraint
     BPOFF       deviation from the ballpark goal constraint
     DEVIATION   deviation from the objective function;

***********************************************************************
  POSITIVE VARIABLES
     X(I), TPOS, TNEG, BPPOS, BPNEG ;

***********************************************************************
  EQUATIONS
     OBJDEF achievement function
     TLIMIT time limit
     DLIMIT distance limit;

********************************************************************
* MINIMIZE
     OBJDEF..  DEVIATION =E=

```

The Alternative Model (continued).

GPNLP2

```
    ( TIMEWT * TPOS ) + ( BPWT * BPPOS );

*********************************************************************
* SUBJECT TO
     TLIMIT..  SUM ( I, X(I) ) - TPOS + TNEG =E= RESPTIME ;
     DLIMIT..  SUM ( I,
     ( 1 - SQRT( (SQR(EPROB(I))) * (X(I)-MIN(I)) / (MAX(I)-MIN(I)) )
         - NEPROB(I) )   *   MCOST(I) ) -BPPOS + BPNEG =E= BPARK ;

*********************************************************************
*  ADDITIONAL CONSTRAINTS involving min and max times allowed.  These
*  keep x in the feasible region as problem iterates, otherwise stops

             X.LO(I) = MIN(I)*1.01;
             X.UP(I) = MAX(I);

*  if region is convex, then no matter where starts, soln should be same
*  Need to start internal because funny things happen on edges

             X.L(I)  = MIN(I)*1.02
                                                   ;
  MODEL GPNLP2 /ALL/;
  SOLVE GPNLP2 USING NLP MINIMIZING DEVIATION;
```

3. The Output
   a. The Current Model

```
GPNLP2
SOLUTION REPORT     SOLVE GPNLP2 USING NLP FROM LINE 150

               S O L V E     S U M M A R Y

     MODEL    GPNLP2                  OBJECTIVE  DEVIATION
     TYPE     NLP                     DIRECTION  MINIMIZE
     SOLVER   MINOS5                  FROM LINE  150

**** SOLVER STATUS      1 NORMAL COMPLETION
**** MODEL STATUS       2 LOCALLY OPTIMAL
**** OBJECTIVE VALUE                0.0151

 RESOURCE USAGE, LIMIT          0.263      1000.000
 ITERATION COUNT, LIMIT        23          1000
 EVALUATION ERRORS              0             0

     M I N O S  ---  VERSION  5.0   APR  1984
     = = = = =
     COURTESY OF B. A. MURTAGH AND M. A. SAUNDERS,
                 DEPARTMENT OF OPERATIONS RESEARCH,
                 STANFORD UNIVERSITY,
                 STANFORD   CALIFORNIA   94305   U.S.A.


 WORK SPACE NEEDED (ESTIMATE)  --     823 WORDS.
 WORK SPACE AVAILABLE          --    1179 WORDS.
 (MAXIMUM OBTAINABLE           --  164974 WORDS.)

 EXIT -- OPTIMAL SOLUTION FOUND
 MAJOR ITERATIONS            1
 NORM RG / NORM PI   5.001E-09
 TOTAL USED               0.28 UNITS
 MINOS5 TIME              0.17 (INTERPRETER -        0.05)

                         LOWER          LEVEL          UPPER          MARGINAL

---- EQU OBJDEF           0.1300         0.1300         0.1300         -1.0000
---- EQU TLIMIT          -INF           30.0000        30.0000         -0.0022

  OBJDEF      ACHIEVEMENT FUNCTION
  TLIMIT      TIME LIMIT

---- VAR X              TIME TO BE SPENT INSPECTING EACH TASK IN BATTERY

           LOWER          LEVEL          UPPER        MARGINAL

G1         0.7070         2.2427         2.8000         EPS
G2         0.7070         2.5660         3.2000         EPS
G3         0.7070         1.0000         1.0000       -0.0056
G4         0.7070         1.6000         1.6000       -0.0001
AG         2.0200         7.2167         8.9000          .
A1         0.7070         1.8000         1.8000       -0.0029
A2         0.7070         1.7816         4.8000         EPS
A3         0.7070         1.7000         1.7000       -0.0042
A4         0.7070         3.4000         3.4000       -0.0011
S1         0.7070         1.1417         3.0000         EPS
S2         0.7070         2.0000         2.0000       -0.0001
S3         0.7070         2.1513         3.5000         EPS
S4         0.7070         1.4000         1.4000       -0.0037

                         LOWER          LEVEL          UPPER          MARGINAL

---- VAR DEVIATION       -INF            0.0151        +INF              .
```

b. The Alternative Model's First Tier.

```
GPNLP2
SOLUTION REPORT     SOLVE GPNLP2 USING NLP FROM LINE 193

                S O L V E     S U M M A R Y

     MODEL   GPNLP2                OBJECTIVE  DEVIATION
     TYPE    NLP                   DIRECTION  MINIMIZE
     SOLVER  MINOS5                FROM LINE  193

**** SOLVER STATUS      1 NORMAL COMPLETION
**** MODEL STATUS       2 LOCALLY OPTIMAL
**** OBJECTIVE VALUE                   0.0

 RESOURCE USAGE, LIMIT           0.419      1000.000
 ITERATION COUNT, LIMIT          4          1000
 EVALUATION ERRORS               0             0

     M I N O S  ---  VERSION  5.0   APR  1984
     = = = = =
     COURTESY OF B. A. MURTAGH AND M. A. SAUNDERS,
                 DEPARTMENT OF OPERATIONS RESEARCH,
                 STANFORD UNIVERSITY,
                 STANFORD   CALIFORNIA   94305   U.S.A.

 WORK SPACE NEEDED (ESTIMATE)  --      330 WORDS.
 WORK SPACE AVAILABLE          --      454 WORDS.
 (MAXIMUM OBTAINABLE           --   164974 WORDS.)

 EXIT -- OPTIMAL SOLUTION FOUND
 MAJOR ITERATIONS            46
 NORM RG / NORM PI   0.000E+00
 TOTAL USED               0.43 UNITS
 MINOS5 TIME              0.39 (INTERPRETER -         0.01)

                          LOWER         LEVEL         UPPER        MARGINAL

---- EQU OBJDEF             .             .             .          -1.0000
---- EQU TLIMIT          30.0000       30.0000       30.0000        EPS
---- EQU DLIMIT         -26.7696      -26.7696      -26.7696        EPS

  OBJDEF      ACHIEVEMENT FUNCTION
  TLIMIT      TIME LIMIT
  DLIMIT      DISTANCE LIMIT

---- VAR X             TIME TO BE SPENT INSPECTING EACH TASK IN BATTERY

          LOWER         LEVEL         UPPER        MARGINAL

A1        0.7070        1.8000        1.8000          .

                          LOWER         LEVEL         UPPER        MARGINAL

---- VAR DEVIATION        -INF            .           +INF            .
---- VAR TPOS               .             .           +INF          1.0000
---- VAR TNEG               .          28.2000        +INF            .
---- VAR BPPOS              .             .           +INF        600.0000
---- VAR BPNEG              .             .           +INF           EPS
```

c. The Alternative Model's Second Tier.

```
GPNLP2
SOLUTION REPORT     SOLVE GPNLP2 USING NLP FROM LINE 191

               S O L V E     S U M M A R Y

     MODEL    GPNLP2                 OBJECTIVE  DEVIATION
     TYPE     NLP                    DIRECTION  MINIMIZE
     SOLVER   MINOS5                 FROM LINE  191

**** SOLVER STATUS     1 NORMAL COMPLETION
**** MODEL STATUS      2 LOCALLY OPTIMAL
**** OBJECTIVE VALUE                     0.0

 RESOURCE USAGE, LIMIT          0.582      1000.000
 ITERATION COUNT, LIMIT        25          1000
 EVALUATION ERRORS              0             0

     M I N O S  ---  VERSION  5.0   APR  1984
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                 DEPARTMENT OF OPERATIONS RESEARCH,
                 STANFORD UNIVERSITY,
                 STANFORD   CALIFORNIA   94305   U.S.A.


 WORK SPACE NEEDED (ESTIMATE)  --      604 WORDS.
 WORK SPACE AVAILABLE          --      838 WORDS.
 (MAXIMUM OBTAINABLE           --   164974 WORDS.)

 EXIT -- OPTIMAL SOLUTION FOUND
 MAJOR ITERATIONS             41
 NORM RG / NORM PI    0.000E+00
 TOTAL USED                0.60 UNITS
 MINOS5 TIME               0.51 (INTERPRETER -        0.06)

                              LOWER          LEVEL          UPPER         MARGINAL

---- EQU OBJDEF                 .              .              .           -1.0000
---- EQU TLIMIT              28.2000        28.2000        28.2000         EPS
---- EQU DLIMIT            -186.2497      -186.2497      -186.2497         EPS

  OBJDEF      ACHIEVEMENT FUNCTION
  TLIMIT      TIME LIMIT
  DLIMIT      DISTANCE LIMIT


---- VAR X             TIME TO BE SPENT INSPECTING EACH TASK IN BATTERY

          LOWER          LEVEL          UPPER        MARGINAL

G1        0.7070         2.8000         2.8000         EPS
G3        0.7070         1.0000         1.0000         EPS
AG        2.0200         8.9000         8.9000          .
A4        0.7070         3.4000         3.4000         EPS
S1        0.7070         3.0000         3.0000         EPS
S2        0.7070         2.0000         2.0000         EPS
S3        0.7070         3.5000         3.5000         EPS

                              LOWER          LEVEL          UPPER         MARGINAL

---- VAR DEVIATION            -INF             .            +INF              .
---- VAR TPOS                   .              .            +INF            1.0000
---- VAR TNEG                   .           3.6000          +INF              .
---- VAR BPPOS                  .              .            +INF          600.0000
---- VAR BPNEG                  .              .            +INF             EPS
```

d. The Alternative Model's Third Tier.

```
GPNLP2
SOLUTION REPORT     SOLVE GPNLP2 USING NLP FROM LINE 208

               S O L V E     S U M M A R Y

     MODEL   GPNLP2               OBJECTIVE  DEVIATION
     TYPE    NLP                  DIRECTION  MINIMIZE
     SOLVER  MINOS5               FROM LINE  208

**** SOLVER STATUS     1 NORMAL COMPLETION
**** MODEL STATUS      2 LOCALLY OPTIMAL
**** OBJECTIVE VALUE               4.8104

 RESOURCE USAGE, LIMIT          0.309      1000.000
 ITERATION COUNT, LIMIT        29          1000
 EVALUATION ERRORS              0             0

     M I N O S --- VERSION 5.0   APR 1984
     = = = = =
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                 DEPARTMENT OF OPERATIONS RESEARCH,
                 STANFORD UNIVERSITY,
                 STANFORD   CALIFORNIA   94305   U.S.A.


 WORK SPACE NEEDED (ESTIMATE)  --      511 WORDS.
 WORK SPACE AVAILABLE          --      709 WORDS.
 (MAXIMUM OBTAINABLE           --   164974 WORDS.)

 EXIT -- OPTIMAL SOLUTION FOUND
 MAJOR ITERATIONS           13
 NORM RG / NORM PI  8.463E-08
 TOTAL USED              0.32 UNITS
 MINOS5 TIME             0.25 (INTERPRETER -        0.03)

                              LOWER          LEVEL          UPPER         MARGINAL

---- EQU OBJDEF                 .              .              .           -1.0000
---- EQU TLIMIT               3.6000         3.6000         3.6000        -1.0000
---- EQU DLIMIT              -7.1981        -7.1981        -7.1981        -1.0000

  OBJDEF      ACHIEVEMENT FUNCTION
  TLIMIT      TIME LIMIT
  DLIMIT      DISTANCE LIMIT


---- VAR X            TIME TO BE SPENT INSPECTING EACH TASK IN BATTERY

          LOWER          LEVEL          UPPER         MARGINAL

G2        0.7070         1.0504         3.2000          EPS
G4        0.7070         1.4691         1.6000           .
A2        0.7070         0.7508         4.8000          EPS
A3        0.7070         1.2784         1.7000          EPS
S4        0.7070         1.2390         1.4000          EPS


                              LOWER          LEVEL          UPPER         MARGINAL

---- VAR DEVIATION            -INF          4.8104          +INF             .
---- VAR TPOS                   .           2.1877          +INF            EPS
---- VAR TNEG                   .              .            +INF          1.0000
---- VAR BPPOS                  .           2.6227          +INF             .
---- VAR BPNEG                  .              .            +INF          1.0000
```

APPENDIX F

GLOSSARY

A. Human Reliability Terminology

1. "Consequence of interest (COI)" is analogous to measure of effectiveness (MOE). MOE is used when the concern is maximizing effectiveness of some positive performance whereas COI is used when the concern is minimizing consequences of some negative performance (for example: human error).

2. "Human error" is any member of a set of human actions that exceeds some limit of acceptability. The set of actions must be defined and the tolerance limits must be established for there to be human error. [Ref 10, p.6]

3. "Human error probability" is the chance that a given task will not be successfully completed by personnel within a required minimum time (if a time requirement exists). This is the reciprocal of human reliability.

4. "Human reliability" is the probability that a task will be completed successfully by personnel within a specified minimum time (if a time requirement exists). [Ref 1, p. 221]

5. "Worker" is the human on the production line who performs the error-prone tasks that potentially effect the finished product. A mistake by a worker that potentially leads to a flawed product is referred to as an "error".

6. "Inspector" is the human tasked to find faulty finished products before they leave the production line. A mistake by an inspector that leads to a flawed product is referred to as a "failure".

7. "System error" is a worker error which evades detection by the inspector and has a cost that is of consequence of interest to the system. A system error is also referred to as a "flawed product".

B. Artillery Terminology

1. A "chief" is the senior man in a crew of men who operate a gun.

2. "Fire(s)", when used as a noun, refers to the shooting of artillery munitions.

3. A "fire mission" is an order from higher authority to shoot one or more rounds of artillery at a target.

4. A "gun" refers to a single artillery cannon weapon system.

5. "Gunnery" refers to the group of skills required of crewmen to fire their weapon.

6. "Maneuver", when used as a noun, refers to infantry or armor elements to which the artillery provides fire support.

7. A "round" is synonymous with the term projectile.

8. A "unit" refers to a battery of artillery. A battery is either six or eight cannon weapon systems.

APPENDIX G

SURVEYS ADMINISTERED TO RESPONDENTS

The collection of the expert judgments from operational personnel was key to solving the illustrative problem. The error probability survey and the time use survey were the two surveys given to the respondents. Respondents were briefed in person prior to working on the survey. The surveys took approximately 45 minutes to complete.

The error probability survey requires a gun chief to compare pairs of errors as to their relative likelihood of occurrence. The comparisons are made among similar type errors within the hierarchical areas defined in Figure 9 in Appendix A. The gun chief is also required to make one direct numerical estimate on the likelihood that his section sets any type of error. The process by which these survey results are turned into probabilities is discussed in Appendix A. The method by which the respondent's judgments are checked for consistency is discussed in Appendix D.

The time use survey requires a gun chief to compare the amount of time taken to perform one inspection task relative another. Comparisons are made among similar type tasks within hierarchical areas defined in Figure 9 in Appendix A. One inspection task which is routinely done in a relatively uniform manner among all gun chiefs is the inspection of the

gunner's sight picture on the gun's aiming reference point. It is assumed that this task takes 2.0 seconds to perform. Using that known value, all other visual inspection tasks are scaled accordingly. The process by which the tasks are scaled from the survey results is discussed in Appendix C.

1. The Error Probability Survey.

FREQUENCY BY WHICH ERRORS OCCUR

(gunner, asst gunner, ammo handlers, FDC)

Which crew element (the one on the left or the one on the right) is most likely to make an error that you must have corrected prior to firing? How many times more likely is the more error-prone element to make an error than the less error-prone element? (Assume daylight firing, shell HE, fuze TIME, Low Angle; with collimator, gunner's quadrant, and safety T.)

(make one "X" per comparison below)

WHICH IS MORE LIKELY ?

how many times as likely?

ERROR in:	>9	8	7	6	5	4	3	2		2	3	4	5	6	7	8	>9	ERROR in:
gunner									==									asst gunner
gunner									==									ammo handlers
gunner									==									FDC / safety T
asst gunner									==									ammo handlers
asst gunner									==									FDC / safety T
ammo handlers									==									FDC / safety T

Indicate below the number of "good" missions to each mission that you must get involved in making a correction on either the gunner, asst gunner, ammo handlers, or FDC (a "faulty" mission is one in which you must get involved to keep shooting accurate.)

How many times as likely are good missions to each faulty mission?

1	1	2	3	4	5	6	7	8	9	10	20	30	40	50	60	>70
faulty mission																good mission

GUNNER ERRORS

Which error (the one on the left or the one on the right) is most likely to occur (prior to your safety inspection) in your gun section? How many more times likely is the more frequent event than the less frequent event? (Assume daylight firing, good conditions, shell HE, fuze TIME, Low Angle; with collimator, gunner's quadrant, and safety T.)

(make one "X" per comparison below)
(Mark only six "X"s on this page)

WHICH IS
MORE LIKELY ?

how many times
as likely?

ERROR in:	>9	8	7	6	5	4	3	2		2	3	4	5	6	7	8	>9	ERROR in:
sight picture									==									bubbles
sight picture									==									df counter
sight picture									==									piece corrn
bubbles									==									df counter
bubbles									==									piece corrn
df counter									==									piece corrn

ASSISTANT GUNNER ERRORS

Which error (the one on the left or the one on the right) is most likely to occur (prior to your safety inspection) in your gun section? How many more times likely is the more frequent event than the less frequent event? (Assume daylight firing, good conditions, shell HE, fuze TIME, Low Angle; with collimator and gunner's quadrant.)

(make one "X" per comparison below)
(Mark only six "X"s on this page)

WHICH IS
MORE LIKELY ?

how many times
as likely?

ERROR in:	>9	8	7	6	5	4	3	2		2	3	4	5	6	7	8	>9	ERROR in:
counter									==									elev bubble
counter									==									cr lvl bubble
counter									==									piece corrn
elev bubble									==									cr lvl bubble
elev bubble									==									piece corrn
cr lvl bubble									==									piece corrn

AMMUNITION HANDLERS ERRORS

Which error (the one on the left or the one on the right) is most likely to occur (prior to your safety inspection) in your gun section? How many more times likely is the more frequent event than the less frequent event? (Assume daylight firing, good conditions, shell HE, fuze TIME, Low Angle; with collimator, gunner's quadrant, and safety T.)

(make one "X" per comparison below)
(Mark only six "X"s on this page)

WHICH IS
MORE LIKELY ?

how many times as likely?

ERROR in:	>9	8	7	6	5	4	3	2		2	3	4	5	6	7	8	>9	ERROR in:
charge									==									shell type
charge									==									fuze type
charge									==									time setting
shell type									==									fuze type
shell type									==									time setting
fuze type									==									time setting

FDC DATA ERRORS

(data is off of Safety T)

Which error (the one on the left or the one on the right) is most likely to occur? How many more times likely is the more frequent event than the less frequent event? (Assume daylight firing, good conditions, shell HE, fuze TIME, Low Angle; with collimator, gunner's quadrant, and safety T.)

(make one "X" per comparison below)

(Mark only six "X"s on this page)

WHICH IS
MORE LIKELY ?

how many times as likely?

ERROR in:	>9	8	7	6	5	4	3	2		2	3	4	5	6	7	8	>9	ERROR in:
deflection									==									quadrant
deflection									==									time for fuze
deflection									==									ammo: chg/sh/fz
quadrant									==									time for fuze
quadrant									==									ammo: chg/sh/fz
time for fuze									==									ammo: chg/sh/fz

2. The Time Use Survey.

COMPARISON OF TIME TAKEN TO PERFORM SAFETY CHECKS ON CREW

Which check (the one on the left or the one on the right) consumes more of your time? How many more seconds does it take to make the longer check verses the shorter check in each of the six comparisons listed below? (Assume daylight firing, good conditions, shell HE, fuze TIME, Low Angle; with collimator, gunner's quadrant, and safety T.)

(make one "X" per comparison below)

WHICH CHECK IS MORE TIME CONSUMING

increased number of seconds it takes to do one task vs the other

#sec	>8	7	6	5	4	3	2	1		1	2	3	4	5	6	7	>8 #sec
gunner									==								asst gunner
gunner									==								ammo handlers
gunner									==								safety T
asst gunner									==								ammo handlers
asst gunner									==								safety T
ammo handlers									==								safety T

DEFLECTION CHECKS

Which check (the one on the left or the one on the right) consumes more of your time? How many more seconds does it take to make the longer check verses the shorter check in each of the six comparisons listed below? (Assume daylight firing, good conditions, shell HE, fuze TIME, Low Angle; with collimator, gunner's quadrant, and safety T.)

(make one "X" per comparison below)

(only mark six "X"s on this form)

WHICH CHECK IS MORE
TIME CONSUMING

increased number of seconds it takes to do one task vs the other

#sec	>8	7	6	5	4	3	2	1		1	2	3	4	5	6	7	>8	#sec
sight picture									==									bubbles
sight picture									==									df counter
sight picture									==									piece corrn
bubbles									==									df counter
bubbles									==									piece corrn
df counter									==									piece corrn

AMMUNITION CHECKS

Which check (the one on the left or the one on the right) consumes more of your time? How many more seconds does it take to make the longer check verses the shorter check in each of the six comparisons listed below? (Assume daylight firing, good conditions, shell HE, fuze TIME, Low Angle; with collimator, gunner's quadrant, and safety T.)

(make one "X" per comparison below)

WHICH CHECK IS MORE
TIME CONSUMING

increased number of seconds it takes to do one task vs the other

#sec	>8	7	6	5	4	3	2	1		1	2	3	4	5	6	7	>8	#sec
charge									==									time setting
charge									==									fuze type
charge									==									shell type/wt/lot
time setting									==									fuze type
time setting									==									shell type/wt/lot
fuze type									==									shell type/wt/lot

FDC DATA CHECKS
(Safety T violations)

Which check (the one on the left or the one on the right) consumes more of your time? How many more seconds does it take to make the longer check verses the shorter check in each of the six comparisons listed below? (Assume daylight firing, good conditions, shell HE, fuze TIME, Low Angle; with collimator, gunner's quadrant, and safety T.)

(make one "X" per comparison below)

WHICH CHECK IS MORE
TIME CONSUMING

increased number of seconds it takes to do one task vs the other

#sec	>8	7	6	5	4	3	2	1		1	2	3	4	5	6	7	>8	#sec
deflec-tion									==									quad-rant
deflec-tion									==									time for fuze
deflec-tion									==									ammo: chg/sh/fz
quad-rant									==									time for fuze
quad-rant									==									ammo: chg/sh/fz
time for fuze									==									ammo: chg/sh/fz

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12. Commander 4
2nd Battalion, 8th Field Artillery
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Thesis
W229671 Warner
c.1 Development of a methodology to optimally allocate visual inspection time.